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Fair climate policies and technical change : essays on the distributional impacts and social acceptability of the path to net zero

Politiques climatiques justes et changement technique : essais sur les impacts distributifs et l'acceptabilité sociale des mesures de neutralité carbone

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Thèse soutenue à Paris-Saclay, le 08 décembre 2022, par

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THESE DE DOCTORAT

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Titre : Politiques climatiques justes et changement technique : essais sur les impacts distributifs et l'acceptabilité sociale des mesures de neutralité carbone

Mots clés : Politiques climatiques ; Inégalités ; Changement technique ; Environnement ; Taxe carbone ; Evaluation des politiques publiques

Résumé : Les politiques d'atténuation du changement climatique vont nécessiter des investissements et générer de nouveaux coûts pour la société. Cette thèse étudie comment ces coûts vont être répartis dans la population, entre les ménages et les travailleurs. Je mêle les approches et les méthodologies pour donner un panorama complet des inégalités induites par les politiques climatiques. La première partie s'intéresse à la consommation des ménages. Le premier chapitre étudie la taxe carbone et les effets pervers de la redistribution de ses revenus aux ménages. Le deuxième chapitre évalue l'impact distributifs d'un ensemble de politiques climatiques en France à l'horizon 2035. La seconde partie étudie l'emploi et les salaires à travers le changement technique. Le troisième chapitre propose un modèle théorique permettant de différencier les directions du changement technique et leurs déterminants. Le quatrième chapitre est une étude de cas d'une technologie bas-carbone.

Title : Fair climate policies and technical change : essays on the distributional impacts and social acceptability of the path to net zero

Keywords : Climate policies ; Inequalities ; Technical change ; Environment ; Carbon tax ; Public policy assessment

Abstract : Climate change mitigation policies will require investments and generate new costs for society. This dissertation examines how these costs will be distributed across the population : households and workers. I mix approaches and methodologies to give a comprehensive overview of the inequalities induced by climate policies. The first part focuses on households consumption. The first chapter studies the carbon tax and the backfire effects of recycling its revenues to households. The second chapter assesses the distributional impact of a package of climate policies in France up to 2035. The second part studies employment and wages through technical change. The third chapter proposes a theoretical model to differentiate the directions of technical change and their determinants. The fourth chapter is a case-study of a low-carbon technology.

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Résumé

Le changement climatique est principalement anthropique, dû aux activités humaines. Une réduction rapide des émissions de gaz à effet de serre est nécessaire pour limiter les dommages, particulièrement sur les populations les plus fragiles qui sont les plus exposées. Cette réduction va nécessiter des investissements massifs et des efforts financiers de tous les agents. Cette thèse étudie comment les coûts des politiques d'atténuation du changement climatique sont distribués entre les ménages et les travailleurs dans le but de limiter les inégalités et ainsi maximiser l'acceptabilité sociale de la transition. Cette thèse est composée de 4 chapitres indépendants répartis entre l'étude des impacts sur la consommation et les revenus des ménages.

Dans le premier chapitre, co-écrit avec Franck Nadaud, nous étudions comment les ménages réagissent à l'introduction d'une taxe carbone suivie de la redistribution des revenus collectés. Nous estimons les élasticités prix et revenus de 40 classes de ménages pour 14 biens et construisons un modèle de microsimulation comportemental. Redistribuer l'intégralité des recettes de la taxe carbone limite la réduction des émissions mais permet d'assurer la progressivité de la taxe qui sinon pèse plus largement sur les bas-revenus et les ruraux. Nous trouvons qu'une taxe carbone de 158€/tCO_{2eq} redistribuée aux ménages à part égale par habitant réduirait l'empreinte carbone totale des ménages de 5,9% et de 7,4% si les 20% les plus riches étaient exclus du recyclage. Nous mettons en lumière l'existence d'un effet pervers (« backfire ») contre-intuitif, pour près d'un quart des ménages qui augmentent leurs émissions après l'introduction de la taxe et du système de recyclage.

Le deuxième chapitre, publié avec Frédéric Ghersi et Franck Nadaud[1], étudie les impacts distributifs d'un ensemble de politiques climatiques permettant d'atteindre la neutralité carbone en France. Ces mesures comprennent notamment une taxe carbone croissante, des subventions aux rénovations thermiques et à l'achat de véhicules électriques. Nous modélisons ces mesures à l'échelle agrégée et à l'échelle des ménages en couplant un modèle de microsimulation avec un modèle macroéconomique. Nous concluons que l'ensemble des mesures est régressif s'il n'y a pas de recyclage des recettes de la taxe carbone vers les ménages. En d'autres termes, les subventions aux technologies bas-carbone ne compensent pas la régressivité de la taxe carbone à court terme. Toutefois, une répartition des subventions ciblée sur les ménages énergivores est

[1] Ravigné, E., Ghersi, F., & Nadaud, F. (2022). Ecological Economics, 196, 107397.

essentielle pour maximiser la réduction des émissions et limiter les inégalités territoriales entre les zones urbaines et rurales.

Le troisième chapitre étudie les déterminants du changement technique. Nous développons avec Mehdi Senouci un cadre de comptabilité du changement technique et de la croissance permettant de désagréger la substitution des facteurs et les différentes directions du changement technique pour diverses industries. Nous concluons que la plupart des industries Européennes et Etats-Uniennes entre 1970 et 2019 innovent pour économiser du capital (*capital-saving*), avec une tendance croissante à innover pour économise sur le travail (*labour-saving*). Nous montrons que les industries ont tendance à innover pour se passer de travail lorsque le coût de celui-ci augmente relativement par rapport au coût du capital. Nous concluons que le changement technique est, au moins en partie, induit par les prix. Nous proposons une extension préliminaire de ce cadre à plusieurs facteurs, incluant l'énergie.

Le quatrième et dernier chapitre, publié avec Pascal da Costa[2], est une étude de cas de l'adoption d'une technologie verte, les camions au gaz naturel, dans la supply chaine d'une grande entreprise. Nous montrons que les conditions réelles d'utilisation, tant économiques que physiques, peuvent nuancer les gains écologiques des camions s'ils le gaz qu'ils utilisent n'est pas biosourcé. Les politiques publiques —- taxes et subventions — si elles sont bien construites permettent d'encourager l'adoption de ces camions et l'utilisation de biogaz pour réduire massivement les émissions du secteur routier.

[2]Ravigné, E., & Da Costa, P. (2021). Energy Policy, 149, 112019.

Summary

Climate change is mainly anthropogenic, and if not limited quickly it will cause huge damage to the most vulnerable populations. Reducing emissions will require massive efforts and investments. This dissertation assesses how the costs of climate change mitigation policies are distributed among households and workers in order to maximise their social acceptability and promote a just transition. The four chapters are independent and divided between the study of household consumption and income.

In the first chapter, co-authored with Franck Nadaud, we study how households react to the introduction of a carbon tax followed by the redistribution of the tax revenues. We estimate the price and income elasticities of 40 classes of households for 14 goods and build a microsimulation model to test the consequences of different tax levels and revenue distribution schemes of the carbon tax. Redistributing the entire carbon tax revenue limits the total reduction of emissions but ensures the progressivity of the tax which otherwise would fall more heavily on the poor and rural. I find that a carbon tax of €158/tCO_{2eq} redistributed as an equal per capita cash transfer to households would reduce the total carbon footprint of households by 5.9%. We highlight the existence of a counter-intuitive 'backfire' effect for almost a quarter of households that increase their emissions after the introduction of the tax and recycling scheme.

The second chapter, published with Frédéric Ghersi and Franck Nadaud[3], studies the distributional impacts of a set of climate policies that would allow France to achieve carbon neutrality by 2050. These measures include an increasing carbon tax, subsidies for thermal renovations and for the purchase of electric vehicles. We model these measures at the aggregate and household levels by coupling a microsimulation model with a macroeconomic model. We conclude that the package of measures is regressive if there is no recycling of carbon tax revenues. In other words, subsidies for thermal renovations and electric vehicles do not compensate for the regressivity of the carbon tax in the short run but are complementary to recycling. A targeted distribution of subsidies to energy-intensive households is key to maximise emission reductions and limit territorial inequalities between urban and rural areas.

The third chapter examines the determinants of technical change. Together with Mehdi Senouci, we create a technical change and growth accounting framework to disentangle between factor substitution and specific factor-saving technical change in the production of various industries. We conclude that most European and US industries

[3]Ravigné, E., Ghersi, F., & Nadaud, F. (2022). Ecological Economics, 196, 107397.

between 1970 and 2019 are net capital-saving with an increasing trend towards net labour-saving. We show that industries tend to be labour-saving when the relative price of labour rises: it shows that technical change is endogenous and price-induced. We add a preliminary extension by including energy, materials and services in the analysis of the direction of technical change.

The fourth and final chapter, published with Pascal da Costa[4], is a case study of the adoption of a green technology, natural gas trucks, in the supply chain of a large firm. We show that the actual conditions of use, both economic and physical, can undermine the environmental gains of natural gas trucks if they do not use biogas. Public policies — taxes and subsidies — if well designed, can encourage the adoption of these trucks and the use of biogas to massively reduce emissions from the road sector.

[4]Ravigné, E., & Da Costa, P. (2021). Energy Policy, 149, 112019.

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Introduction

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Ils ne bougent pas.

Samuel Beckett, *En attendant Godot*

Climate change is an equity issue. It is now established with high confidence that climate change is anthropogenic.[5] Humanity is already facing warming of almost 1 degree compared to pre-industrial times and it seems hard to imagine that it could be limited to less than 1.5 or 2 degrees at best (IPCC WGI, Masson-Delmotte et al. (2021)). The consequences of climate change will be severe and already are. The risks and disasters that will come are not just theoretical — a higher probability of extreme events, higher average temperatures, and more severe precipitation anomalies — but will affect countries and populations, killing and displacing millions. This damage will add to and even exacerbate the ravages of poverty, epidemics, and wars (IPCC WGII, Pörtner et al. (2022)). As Kasperson and Kasperson (2001) wrote more than two decades ago "The lesson from climate change is a more general one: risks do not register their effects in the abstract; they occur in particular regions and places, to particular peoples and to specific ecosystems." (p275). In the same way, emissions are emitted by real people to fulfil their basic needs and achieve some comfort.

Pollution — local or global — is a textbook case of negative externality: the agent who emits a ton of CO_2 causes harm and costs to others globally. More generally, an externality occurs when the action of an agent affects the utility or production possibilities of another agent (Baumol et al., 1988). In the case of climate change, it can even be said that the largest emitters bear a relatively small share of the consequences. To date, about 57% of total cumulative anthropogenic greenhouse gas emissions come from developed countries (IPCC, WGIII, Shukla et al. (2022)). Yet it

[5]Most of the public and media attention is on climate change and greenhouse gas (GHG) emissions as the defining issue of our century. However, five more planetary boundaries are about to be transgressed along with climate change: nitrogen cycle degradation, and land system change (Rockström et al., 2009) ; the rate of biodiversity loss (Steffen et al., 2015); plastic pollution (Persson et al., 2022) and green water (soil moisture) (Wang-Erlandsson et al., 2022). To the best of our knowledge, there is little literature on policies addressing non-climate planetary boundaries transgression.

is the developing and least developed countries of the Global South that will bear the brunt of the effects of climate change. These countries are obviously reluctant to limit their emissions as it would prevent them from developing, meeting the basic needs of their populations, and adapting to the inevitable consequences of climate change. The extent to which developed countries must limit their emissions and help South countries to limit theirs is a point of international tension. For example, China has emitted little compared to the North's historical emissions, but it currently has large emissions with major development gaps between its cities and rural areas. The contrasting distribution between the responsibilities in climate change and the climate change related damages is one of the main factors of climate inaction.

The same problem arises at the national level: low-income households have a much smaller carbon footprint than high-income households. A French household in the bottom 10% of income emits about 15 tons of CO_{2eq} per year, which is 2.2 times less than the average household of the top 10% households, about 33 tons of CO_{2eq} (Pottier et al., 2020). Even in Western countries, the poorest households suffer more from the consequences of global warming and pollution (Hajat et al., 2015). In short, the distribution of responsibilities in emissions does not coincide with the distribution of damages.[6]

The distribution of mitigation costs — policy-induced cost for the most part — does not coincide either with the distribution of income. The poorest will bear a disproportionate share of the costs compared to their income (Vona, 2021). Regardless of the cost allocation rule, unequal distribution of the burden among households is problematic. The first reason why is ethical: because justice can be considered a goal in itself (Fleurbaey et al., 2019). The second reason why it is problematic is economic: it increases the total cost of the transition. For instance, if the guiding principle of cost allocation is the minimisation of the total cost, then mitigation should rely more heavily on agents with low marginal cost of abatement to equalise marginal costs overall. If this cost allocation does not match income distribution and thus investment capacity, then it might increase the total cost of transition. As an example, a low-income household is likely to drive an old fuel-guzzling car: it would be cost-efficient for the society to replace it, except that these households might not be able to invest in a new efficient car. Either society must help them to do so, which creates administrative and transaction costs, or another household — with a higher marginal cost of abatement — must limit these emissions to make up for the missed savings opportunity. The third reason is political: policy-induced inequalities reduce citizen support for the transition and thus its feasibility (Carattini et al., 2019): the *Gilets Jaunes* protests in France in 2018 are a case in point.

The distribution of responsibilities and consequences of climate change do not coincide, nor do the mitigation costs and income. Balancing these distributions will not automatically happen. Policy-makers must thus address these issues and the various root

[6] See Drupp et al. (2021) for a comprehensive overview.

causes of inequalities among countries, populations, and households. Climate change is an equity issue and climate change policy as well.

This thesis contributes to the debate on the relationship between climate policies and equity, with a focus on national inequalities in Western countries, mainly France. We examine the effectiveness of different policy measures to reduce emissions – targeting households or encouraging firm innovation – and the distribution of the costs among households and workers. We determine how policy measures can reconcile the twin goals of equity and emission reduction using a variety of methodological approaches.

The remainder of this introduction outlines the main principles of mitigation strategies, introduces various policy instruments and their mixed distributional consequences, and finally addresses the redistributive measures to offset distributional effects. The final section states the contributions of the different chapters of this thesis.

1 Long-term strategy and short-term tools

The last IPCC WGI report (Masson-Delmotte et al., 2021) estimates that no more than 1150 $GtCO_{2eq}$ are to be emitted from the beginning of 2020 to likely limit the increase in temperature to 2°C. This remaining carbon budget represents about 25 years at the current rate of emissions ($\simeq 1,300tCO_{2eq}$/sec).[7] It implies reducing the volume of carbon emissions very rapidly and reaching net zero anthropogenic CO_2 emissions to stabilise the temperature.

The logic behind the Kyoto Protocol was to break down the remaining carbon budget between countries. It assigned binding reduction targets to developed and in transition countries (so-called Annex 1 countries). The Paris Agreement is based on voluntary commitments, which each country breaks down by sector. This is the case in France, where each sector is to reduce its emissions as per the *Stratégie Nationale Bas Carbone* (SNBC, Low-Carbon National Strategy). At the sectoral level, the volume of emissions can be expressed as the volume of final demand multiplied by the carbon intensity of the production of this good. Reducing the volume of emissions can be achieved through two levers: reducing the final demand — that is, avoiding, shifting or improving the consumption which is defined as *sufficiency* in the IPCC WGIII report (Shukla et al., 2022)[8] — or reducing the carbon intensity of the production with supply-side measures to reach a *decoupling* between production and emissions.

The first lever of emissions reduction is *sufficiency*, the decrease of final demand of the sector output. Consensual examples of sufficiency in the transport sector would be: working from home to avoid a car trip to the workplace, shifting from a private car trip

[7] https://www.mcc-berlin.net/en/research/co2-budget.html provides a Carbon Clock with the remaining carbon budget.

[8] It is defined in the summary for policymakers as "a set of measures and daily practices that avoid the demand for energy, materials, land and water while delivering human well-being for all within planetary boundaries." (IPCC, AR6, 2022, SPM, WGIII, p35, Shukla et al. (2022)).

to public transportation, or improving the car from a combustion engine to an electric one. Purchasing a more efficient car is considered a sufficiency strategy according to this definition, as it reduces the final fuel demand. These three examples may shift emissions to another sector but reduce the final demand for fossil energy and thus the emissions of the sector.

At the sectoral level, the *decoupling* lever, which is a supply-side view, means reducing the carbon intensity of the final good. Firms can reduce energy use by technical change, substitute it for another factor (capital or labour) or substitute fossil fuel for clean energy. The carbon intensity of the final good will have decreased but not the volume of goods produced. The electrification of industrial processes and the development of renewable energies are major tools for the decoupling of production and emissions in most sectors, as well as the reduction of waste in the more global process of circular economy which plays on synergies between processes or firms to reduce the carbon and material footprints of production.

One might notice that a reduction in the carbon intensity of production of a good can be offset by an increase in the final demand for that good, leading to an increase in the volume of emissions of the sector. Emissions may also shift from the consumption to the production stage. This is referred to as the partial decoupling of the sector's emissions.

At the sectoral level, the distinction between sufficiency and decoupling is clear, and there is a consensus in the literature that they should both be used — in proportions that vary between sectors. For instance, the IPCC reports that sufficiency accounts for 10% of the energy demand mitigation potential of new buildings.[9] Some policy measures work simultaneously on intensity reduction and demand reduction such as cap-and-trade (see next section).

We can extend the decomposition at the global level. Reducing the aggregate volume of greenhouse gas emissions can be achieved through the same two levers: reducing the volume of total activities, that is, total production or consumption, or reducing its average carbon intensity. However, the analysis is slightly different because of some general equilibrium effects.

There is growing literature on both providing decent living standards for all and reducing energy demand (Millward-Hopkins et al., 2020; Rao et al., 2019; O'Neill et al., 2018). This strand of research has several points in common with the decoupling strategy and the rest of the mitigation literature. First, countries in the South will need to increase their energy consumption to meet their basic needs (building roads, hospitals, connecting households to water and electricity, developing air conditioning, etc.) (Hickel and Hallegatte, 2022; Boston, 2022; Hickel and Kallis, 2020; van den Bergh, 2011; World Bank, 2012; Inter-American Development Bank, 2021). Secondly, this approach assumes strong progress in energy efficiency, green technologies and renewable energies. Millward-Hopkins et al. (2020) estimates that we could meet the basic needs of a population of 10 billion people with 40% of current global energy use. Such a decrease would

[9] C7.3, SPM, IPCC WGIII, Shukla et al. (2022)

require massive use of the best current energy production technologies, a doubling of renewable energy production, and development of renewable energy storage systems, and a drastic reduction in energy demand (up to 95% of the energy consumption of the richest countries). It does assume a massive effort towards decoupling basic consumption and energy use since reducing the energy use of Global North countries by 95% with the same carbon intensity would mean failing to meet the basic needs of the population.

At the aggregate level, that is, in general equilibrium, the non-consumption of a good, say renouncing a long-haul flight, frees up income that the household will spend elsewhere. It will increase the final demand for another good, say a local cycling holiday and leisure activities. However, note that the overall income level has not fallen, but the average carbon intensity has decreased. A decoupling between income and emissions has therefore occurred through a reallocation of consumption to less carbon-intensive goods. Let us draw on that point: decoupling does not necessarily imply technical change, but incorporates a large part of the substitution of one demand by another. The question remains in the literature: can we expect a total decoupling of consumption through a reduction in the sectoral carbon intensity of production or a reallocation of expenditure towards less carbon-intensive goods?

The literature is fairly unanimous that many countries have achieved relative decoupling — reduction in the carbon intensity of production that is more than offset by growth in activity. On the contrary, absolute decoupling — reduction in intensity that exceeds the economic growth rate leading to the decrease of emissions volume — has rarely been observed (Vadén et al., 2020; Haberl et al., 2020; Hubacek et al., 2021). Le Quéré et al. (2019) examines 18 developed countries that have reduced their emissions by a median 2.4% between 2005 and 2015. Two of the key drivers of the decoupling are the ambitious development of renewable energy and the low economic growth during the period. These studies show little evidence of absolute decoupling in the past, but at the same time, they point out that little to no ambitious policies have been implemented during the observed period. What is certain is that absolute decoupling would require a massive and unprecedented break in the historical trends in emissions. It is therefore difficult to give a definitive answer to the question of whether there will be absolute decoupling in the future.[10]

The impossibility of decoupling consumption and emissions in time to remain within planetary boundaries is the starting postulate of so-called "degrowth economics", which makes demand reduction the main lever for reducing emissions on an aggregate scale (Kallis et al., 2018; Kallis, 2011). Several degrowth definitions can be found in the literature that go beyond the IPCC definition of sufficiency. van den Bergh (2011) identifies five of them: GDP decrease, consumption decrease, physical footprint decrease (material and energy), work time decrease[11], and radical degrowth which combines all

[10] Way et al. (2022) finds that it is likely that transitioning avoid such costs that it might result in a net economic benefit, an even stronger results than decoupling.

[11] This path has not been studied much yet, but existing studies point to a correlation between working hours and ecological footprint, see Nässén and Larsson (2015); Knight et al. (2013); Devetter and Rousseau (2011).

or part of the previous definitions.[12] Let us note that this kind of degrowth cannot be compared to periods of recession and crisis because sufficiency assumes strong popular consensus — democratic debate is at the core of this literature — and carefully planned decrease in demand (as opposed to the economic collapse of some sectors regardless of their carbon footprint or their social utility).

If the level of total decoupling is not sufficient to abide by the remaining carbon budget and the carbon capture and storage technologies allowing to remedy a carbon overshoot are not available in time[13], then we need to reduce the volume of consumption.

Let's do a thought experiment and assume these hypotheses are true: we are in a world where we have decoupled everything we could have.[14] That means that the Global South countries have developed as efficiently as possible. Hence, to reach a certain emissions target (say the natural carbon sinks capacities) we need to cut energy consumption globally. We need to renounce some energy consumption and not substitute one expense for another since we already are at the limit and we have assumed that all human activities are to some extent carbon-emitting.[15] Let us call it "strict" sufficiency. For instance, it would be to reduce the heating from 20 to 19 degrees at home, without using the surplus income or investing it (through savings in banks) since that would allow for more production. What does one do with their surplus income? Given emissions cannot increase any more, a transfer to Global South countries to support their development would mean that we can still substitute a carbon-intensive consumption by another one less emitting. This has already taken place in our experiment. Work less thus earn less? One would substitute work for leisure, and according to the hypothesis of this thought experiment, i) leisure is — even if very little — carbon emitting and ii) all agents have already substituted as much work by leisure as possible.[16] Households have then extra-income in their hand, that they cannot spend. Then they might as well burn it, if not for the carbon it would emit.

Let us pursue this thought experiment and think about its implementation. Governments would need to enforce individual carbon quotas. For each expenditure — of which they would know exactly the carbon footprint — the quota would be deduced and consumption would be impossible when it reaches its (annual ?) limit.[17] These individual

[12] We refer to van den Bergh (2011) for a full review of their differences and possible counterarguments.

[13] Both these hypotheses are not unlikely.

[14] This assumption is important, since firstly, the margins of progress in energy efficiency with constant technology are considerable, and secondly that without any decrease in carbon intensity, it would mean decreasing consumption and GDP in the same proportion as the carbon reduction we need, that is more than 90% in Western countries.

[15] If not, it would mean there is a "free" decoupling solution.

[16] Consider a non-separable utility function between consumption and leisure time. The past decoupling constraint of this thought experiment has lowered the marginal utility of consumption and has shifted the equilibrium towards less work and more leisure.

[17] Follow tricky questions that we are only scratching the surface of, for instance, how do we distribute these quotas; how do we help those who have spent it and no longer have enough to eat or heat their homes. These are provocative questions that need no answers: as democratic consensus is key to the emergence of such systems and would work out answers.

quotas would be negotiated at the level of each country and at the international level to limit global energy demand. Two difficulties emerge. First, building the broad consensus required to implement these measures seems unlikely, given past experiences of binding environmental measures. Second, the failure of past international negotiations to agree on emissions reduction targets or decide on substantial transfers from North to South to mitigate climate change shows enough what a herculean task would be to reach a global agreement to limit global demand as described. The level of societal trend break required to achieve this system seems no less a leap of faith than absolute decoupling.

The conclusion of this thought experiment is that sufficiency at the global scale is a strong decoupling of production and emissions. Indeed, the implementation of "strict sufficiency" and such coercive measure appears impossible and are ruled out. What is meant by sufficiency at the global scale is then substitution: substitution of carbon-intensive goods by low-emitting consumption including leisure. A global decoupling includes a substitution of leisure and labour as well. Hence the difference between decoupling and sufficiency at the aggregate level is more a difference in level than in nature.

Once we have established that the two levers — sufficiency and decoupling — do not differ in nature at the aggregate level, we may discuss the implementation of these two levers at the sectoral level. The two strands of literature — focusing on decoupling and sufficiency, or to call them differently, degrowth and green growth — reach a certain consensus on the measures to be implemented in the short and medium terms: quotas and standards, or appropriately high prices, can ensure that carbon intensity is reduced or, if necessary, supplemented by reductions in production or consumption when efficiency measures are not cost-effective.[18] The good news is that the adoption of such specific measures does not require that all agents share the same final goals (Hickel and Hallegatte, 2022).

This dissertation reviews such policies and assesses their impact on households and the level of inequality. It studies how to design measures that are both efficient and fair in dynamic models in static microsimulation (Chapter 1), but also with economic growth in France (Chapter 2). Chapters 3, and 4 examine the price of factors, and in particular the carbon tax, as an incentive for innovation that can accelerate decoupling.

2 Overview of climate and environmental policies

2.1 Different types of instruments

Climate and environmental policies can be divided into three main categories: incentive-based instruments, regulatory instruments, and voluntary measures.

[18]See Cosme et al. (2017) which reviews the declining literature and summarises the policy tools proposed in the articles. These overlap with the classic environmental policy tools.

Incentive-based instruments are an application of Pigou's theory of externalities. They provide an appropriate financial incentive to decision-making: they are taxes, subsidies, and permits.

The *Pigouvian tax* transfers the damage suffered by society to the polluter who will act accordingly to reduce the externality (Pigou, 1920). The optimal tax rate is thus equal at the marginal damage caused. A carbon tax is a good example of a Pigouvian tax: the carbon tax included in the price of gasoline covers the climate change damages resulting from the consumption of this litre of gasoline in addition to the total gasoline consumption.[19] The first effect of the Pigouvian tax is sufficiency, that is, the reduction in demand. The second effect is to favour efficient or clean technologies — e.g. an electric car over a diesel car. Similarly, if public transportation is cheaper than a congestion ticket that applies to cars, it creates an incentive to switch to other modes of transportation.[20] In a nutshell, that is decoupling transport from emissions. This ensures that only those who really need their personal vehicle use it and they do so in the least emitting way.

A subsidy works similarly to a Pigouvian tax, in prosaic terms it is the carrot versus the stick. A tax disincentives the activities that generate a negative externality. Symmetrically, a subsidy creates incentives for activities that generate positive externalities (or relatively less negative externality). A tax incentive firms to reduce their emissions as long as the marginal cost to do so remains below or equal to the level of the tax (beyond which, it is cheaper to be taxed than to reduce these emissions). A subsidy lowers the price of a clean good and thus of abatement to reflect the relative gain to society compared to the dirty good, thus increasing the volume of the positive externality. A bonus for the purchase of an electric vehicle would give it a financial advantage compared to internal combustion engine vehicles. Note that a subsidy for a clean technology achieves the desired outcome only if the dirty alternative is costly for the firm. A subsidy would not work to reduce an untaxed pollution, for instance, no subsidy would incentivise drivers to purchase a catalytic converter.

A cap-and-trade system provides a monetary incentive to reduce emissions. It is a quantity-based instrument, requiring an emissions threshold (a quantity) instead of a direct price (tax or subsidy). The total quantity of emissions is to be distributed among agents in the form of quota allowances or emissions permits. These allowances are tradable: agents can exchange these allowances in a specific marketplace according to their needs in an emission trading system (ETS). The balance of supply and demand sets the price at any given time. Similarly to taxes, firms that can reduce their emissions at a cost per ton of carbon that is below the market price will do so and then sell their extra allowances to firms with expensive emission reduction costs. The ETS solution is the ideal tool to favour both decoupling and sufficiency because it considers each individual or firm's capabilities to reduce emissions and secures a predetermined threshold. The main problems are the allocation of allowances (whether they should be free or auctioned,

[19] That is, the marginal damage created by gasoline consumption.

[20] Such a scheme can also cover other negative externalities. The London congestion charge aggregates the damage of GHG emissions, pollutants, noise and congestion created by cars in the price of a traffic ticket, hence favouring the switch to public transports inside the city.

what information is needed to allocate free allowances or determines the cap) and transaction costs (for the government, developing and maintaining a marketplace and secured allowances, and for firms, planning mitigation actions at the right price to sell allowances with a profit). Since the implementation of the ETS in Europe, too many free allocations have limited the efficiency of the cap-and-trade in the first years of its existence (Quirion, 2021). Note that even when allowances are not tradable[21], an implicit carbon price is imposed on production costs mimicked by a tighter energy supply.

Coase's approach (Coase, 1960) is somewhat similar to cap-and-trade — but still is not a proper incentive-based instrument. It assumes the allocation of property rights to pollution. Based on these property rights, the polluters and the polluted ones can negotiate and achieve the least costly situation. If the pollution rights belong to the polluted, who are interested in breathing clean air, the polluters can compensate them in return for continuing to pollute.[22] Conversely, even if the polluter owns the right to pollute, the polluted ones can get the firm to stop polluting.[23] In theory, the allocation of rights to one or the other agent does not affect the optimality of the outcome, it merely creates a basis on which pollution and money transfers can be negotiated but it obviously has different financial and distributional impacts. However, such a solution would not be feasible for several reasons: it implies that the ownership of the commons should be attributed to someone, the state or private agents and it requires direct negotiations between all agents, which is both costly and impractical to organise.

In contrast to incentive-based solutions, command-and-control regulatory instruments impose a uniform emission standard on all agents (e.g. performance standards, e.g. fine particle emission limits for new vehicles, maximum fuel consumption or non-tradable emissions quotas), or a particular technology to be used (design standards, e.g. catalytic converters on new vehicles or LED lighting). Regulations have a cost for the consumers, reflecting the cost of abiding by these standards for firms. Firms face an implicit price of carbon, different for each agent depending on the ease with which it can comply.

The third category of instruments is voluntary commitments. Citizens or non-governmental organisations can act voluntarily to reduce emissions. They allow intrinsic motivations and climate concerns to inform their decision-making, without incentives or imposed regulations. However, they may respond to an information campaign or additional information (organic, no animal suffering, local, fair prices for producers, etc.).

The public sector, directly or through state-owned enterprises, can reduce emissions or invest in green technologies or infrastructure (especially in transportation or power

[21] It is then closer to a regulatory approach, see below.

[22] Their offer is accepted if the compensation is greater than the damage. The polluters can make such an offer if they make higher profits from the pollution than the damage suffered by other agents. Otherwise, the pollution is prohibited.

[23] They can compensate the loss of profit induced by the reduction of the pollution to the extent of the benefit they get from clean air.

generation with a mandatory renewable portfolio) necessary for the transition but too costly for a private operator. They pave the way for the decarbonisation of the economy rather than investing directly in substitution or fuel efficiency.

Green technologies can face market failures that require specific policies (Goulder and Parry, 2008). Without an efficient patent system, firms are less interested in investing heavily in R&D to abate their emissions. They need assurance that the revenues from their research will cover the development costs. Duguet and Lelarge (2012) show that patents premium influence the direction of technical change by affecting the allocation of R&D investments. Specific R&D subsidies, better patent rules and international agreements can improve the attractiveness of developing new technologies in addition to the incentives or command-an-control already mentioned. Conversely, a lower degree of appropriation of technology by patents increases knowledge spillovers and facilitates the reduction of emissions (Fischer and Newell, 2008). The adoption of technologies by firms and consumers requires easily accessible information about available technologies and their efficiency. Compulsory information about energy is key to decision-making, e.g. energy performance diagnosis for housings or energy consumption of electronic appliances.[24]

2.2 Choosing the right instrument

Is there a perfect climate policy instrument? The theoretical literature has often tended to prefer incentive-based solutions to regulatory ones. The reasons are plenty, but the main one is efficiency. Incentives allow agents to tap various abatement channels with minimal marginal cost. Moreover, taxes and auctionable allowances (or quotas) raise revenues for the government (see Cropper and Oates (1992) for a complete review of market-based advantages over regulatory instruments). In a first-best world, incentive-based instruments — especially a Pigouvian tax or cap-and-trade — appear to be the silver bullet of climate policy. However, policy-makers belong to a second-best world with multiple market failures and more criteria than cost-effectiveness to consider for policy design.

Theoretical models tend to compare a flexible tax, estimated at marginal damage, to a narrowly defined regulation imposing a specific technology mandate. In these conditions, along with pure and perfect competition, the tax is always preferred to the regulation. However, under imperfect information, a standard which does not require precise knowledge of the agents' costs structure might be superior to a tax. Likewise, a tax and a tradable allowance market are theoretically equivalent. But under uncertainty, where one struggles to estimate precisely marginal damages of century-distant catastrophic events, Weitzman (1974) shows that one tool may be superior to the other. It all boils down to the slopes of costs and damages functions — i.e. the

[24] Too precise information about the energy consumption of electronic appliances, e.g. fridges, can have the perverse effect of encouraging the purchase of cheap low-efficiency appliances (d'Adda et al., 2022).

difference in result caused by the uncertainty of a few percentage points on damage estimation — and especially, on potential threshold effects.[25]

In the case of climate change, policies' robustness to uncertainty is a key feature. There is large uncertainty in the estimation of climate change-related damages — diverse in nature and spread over time — aggregated into a single monetary value, the *social cost of carbon*. The social cost of carbon is widely used to design and calibrate climate policy as it represents the marginal benefit of not emitting a ton of carbon. Estimates are mostly computed using Integrated Assessment Models (IAM) (Nordhaus, 1991) which bring together economic and climate models responding to each other. The range of estimates of the social cost of carbon across models is wide (Quinet et al., 2009) and highlights the challenges in setting a uniform carbon tax.[26]

Policymakers deal with more than one market failure at a time, among others : climate change, air pollution, innovation deficit, information deficit, non-perfectly rational agents, dependence on infrastructure, moral hazard, etc. It justifies using multiple instruments simultaneously as an application of Tinbergen's rule (Tinbergen, 1952). It states that n different objectives must be addressed by at least n tools. The most effective approach is therefore to combine different tools (see among others Edenhofer et al. (2021); Kern et al. (2019); Fischer and Newell (2008), for a more complete review see chapter 13.7 of the IPCC WG III AR6 (Dubash et al., 2022)).

Climate policies are *in fine* judged by the reduction in emissions, that is, effectiveness. Carbon prices have led to emission reductions (Andersson, 2019; Leroutier, 2022) even if in small proportions compared to the climate targets (Green, 2021). Carbon prices have also spurred clean innovations and patents (Aghion et al., 2016; Calel and Dechezlepretre, 2016). Tradable allowances show limited effectiveness, mainly due to the overallocation of free allowances, but also because they have incentivised investment that would have been made even without the policy (Quirion, 2021). Subsidies show mixed results depending on their scope. Energy efficiency subsidies yield significantly lower emissions reduction than expected. The energy efficiency gaps have multiple drivers, including rebound effect, biases in the ex-ante engineering assessments and unobserved parameters (Fowlie et al., 2018; Allcott and Greenstone, 2012; Gillingham and Palmer, 2014). However, subsidies to renewable energy have been a success in providing carbon-free electricity (Nicolini and Tavoni, 2017). Norms and regulations have proven effective too, for instance, in reducing fuel demand in transport sectors in the US through the car energy efficiency standards (CAFE, Corporate Average Fuel Economy) (Geller et al., 2006; Greene, 1998).

The choice of an instrument is even more difficult when integrating competing criteria into policy design. Peñasco et al. (2021) carries out a systematic review of the literature to classify a dozen emission reduction tools according to 7 criteria:

[25] For a more recent review of the respective advantages of price versus quantity based instruments, see Hepburn (2006).

[26] See Pindyck (2013) and Keppo et al. (2021) for a critical review of the IAM landscape.

environmental effectiveness to meet the emission reduction target, technological effectiveness to meet the target in terms of installed capacity, deployment of the technology, cost-effectiveness, innovation outcomes, impacts on competitiveness, distribution of costs and benefits, political acceptability and feasibility.[27] Along with Goulder and Parry (2008); Fullerton (2001), it concludes i) that no tool is superior to the others: there is no silver bullet; ii) the tool performance on each dimension depends heavily on its design; iii) the trade-off between criteria, fairness and cost-effectiveness for instance, requires democratic consensus on the weight to give each different dimension; iv), policy instruments interact with multiple existing policies dealing with various market failures. It might help to combine instruments' strengths in a multi-instrument policy package. To summarise, policy design is key.

Chapters 1 and 2 of this dissertation show that the design of policy has large impacts on their effectiveness and distributional consequences. The targeting of subsidies to low-carbon technologies for households and the use of carbon tax revenues. Chapter 4 finds that the scope of a carbon tax, including or not upstream emissions in the final value, can influence environmental effectiveness and emission reductions.

3 Direct distributional impacts

Climate policies can be assessed on several dimensions, which may undermine or reinforce each other. This section focuses on fairness, main measures — carbon taxes, subsidies and standards — are examined in turn. It shows that all dimensions are linked to one another: competitiveness, political acceptability or technical change all have distributional impacts.[28]

3.1 Carbon taxes

A carbon tax results in an increase in the cost of fossil fuels, which has important distributional consequences for households that consume a higher energy share relative to their income. In industrialised countries, direct energy consumption (fuel, heating, etc.) grows less than linearly with income. The biggest polluters are the richest households, but poor households have a more carbon-intensive consumption: they spend a higher proportion of their income on energy and, therefore on carbon if priced — explicit or implicit. This is why the carbon price is often called 'regressive' in contrast to income tax which is progressive and whose rate increases with income.

However, there are mixed results on the empirical regressivity of the carbon tax. The studies focusing on France find that energy taxes are regressive (Berry, 2019; Douenne,

[27] Goulder and Parry (2008) adds to the criteria already mentioned the interaction with other taxes already in place, the administrative and implementation costs, the distribution of costs and benefits (between firms and between households, etc).

[28] Some literature reviews give a more complete overview than the following one, please seeVona (2021); Drupp et al. (2021); Wang et al. (2016).

2020; Combet et al., 2010). A tax on fuel also appears to be regressive in industrialised countries, even if the effects are fairly small (Lamb et al., 2020). Nevertheless, if the carbon tax encompasses all the emissions induced in consumption — the total carbon footprint — then the tax tends to become more neutral or slightly progressive in a certain number of countries (Feindt et al., 2021; Isaksen and Narbel, 2017). Part of the literature contests that the carbon tax is even regressive at all. It might be because they consider indirect effects along with the tax, such as social transfers to low-income households or employment effects (see section 4). Carbon taxes are mostly progressive in developing countries where, on the contrary, the richest households are more energy-intensive (Dorband et al., 2019; Steckel et al., 2021).

Overall, regressivity is a valid concern for carbon pricing in Global North countries. It then requires specific studies per country before implementing it since the magnitude and significance of the effect depends on the scope of the tax and local specificity (Flues and Thomas, 2015; Wang et al., 2016; Ohlendorf et al., 2020; Klenert et al., 2018b).

When energy taxes are indeed regressive, they cause so-called "vertical" inequalities among households: they place a disproportionate burden on the poorest, who are at the bottom of the "income ladder" (Chiroleu-Assouline, 2015; Metcalf, 1998; Poterba, 1991).

Carbon price also creates "horizontal" disparities within income classes. These are most often territorial disparities between rural and urban areas and generational (Baranzini et al., 2000). These disparities may exceed in amplitude the disparities between income classes (Fischer and Pizer, 2019; Cronin et al., 2019; Pizer and Sexton, 2019). They have received late attention in the literature (see Fischer and Pizer (2019) and Hänsel et al. (2021) for recent literature reviews) but are at the core of protest against carbon taxes as in the French Gilets Jaunes (Douenne and Fabre, 2022, 2020; Jetten et al., 2020).

3.2 Subsidies

We differentiate between two types of subsidies: purchase subsidies for households and subsidies for companies, especially for R&D. Purchase subsidies have distributional impacts because they are more likely to be allocated to richer households. The most common subsidies are bonuses for the purchase of electric vehicles, for housing improvements (e.g. insulation, boiler replacement) or for renewable energy production (installation of solar panels or a selling premium on the produced electricity). Empirical studies find that the effects of the subsidies have been regressive, benefiting relatively more the wealthier (see Lamb et al. (2020) for a review).[29] As there is no minimum income threshold to benefit from subsidies, we may identify two implicit reasons for unequal allocation: i) investment barrier, the remaining investment after the subsidy is still too large for the poorest households, they cannot access loans, or the amount to be paid upfront is too large even if fully reimbursed later on; ii) the information and support to participate in such schemes — sometimes paperwork-heavy — is difficult to

[29] Caulfield et al. (2022) also finds that electric vehicles (EV) subsidies are regressive in Ireland. See DeShazo (2016) for a review of previous papers on EV subsidies.

access for the poorest or less educated. A striking example is the thermal insulation, solar panels and electric vehicle subsidies in the US. These subsidies are provided in the form of tax breaks, it means that non-taxable households are effectively excluded from the measure. Between 2006 and 2013, 60% of these tax cuts benefited the richest 20% of households (Borenstein and Davis, 2016). West (2004) finds that in the US, subsidies to new and less polluting vehicles are even more regressive than a tax on gasoline.

Nevertheless, some successes are to be celebrated and replicated. First, investment support can take the form of a bank guarantee, interest-free loans for households excluded from traditional financing channels, and direct purchase subsidies (without or limited upfront payment). In the UK, the "Affordable Warmth Obligation" fights fuel poverty. It requires energy suppliers to inform eligible households (which includes all beneficiaries of social benefits) about the program and to finance almost entirely the investment in thermal renovation and renewable energy production appliances (Sovacool, 2015). It solves information access and investment capacity failures all in one. An interest-free loan would have solved only the investment failures. This example also points out the necessity for means-tested subsidies — with an income threshold — to focus the measure on the most vulnerable.

Investment subsidies in R&D allow firms to innovate more and develop their technical solutions. It can result in new products, which may be more or less expensive, or the development of a sector (solar panel for instance) and thus the decrease in the price of a specific technology. Lower prices for low-carbon technologies reduce investment barriers for households and thus reduce inequalities.

3.3 Standards

Command-and-control policies impose a performance standard or a technology mandate. The better environmental performance is passed on in prices, therein distributional impacts of standards are fairly similar to those of carbon pricing. However, standards are less cost-effective than taxes because they impose a technology, which might not be the one with the least marginal cost for the agent. They only activate the energy-efficiency lever, that is decoupling, and do not incentivise for sufficiency and demand reduction.

Let us take the example of the US car fuel efficiency regulation CAFE (Corporate Average Fuel Economy) which regulates the average distance travelled per unit of fuel within a carmaker fleet. CAFE creates an implicit carbon price which is 1.5 to 5 times higher per avoided ton of CO_2 than a tax (Jacobsen, 2013; Austin and Dinan, 2005). Then, in addition to bearing a relatively higher burden of rising energy prices, the poorest households face the risk of remaining captive of polluting cars. First, because access to more efficient — and more expensive — cars is then more difficult for the poorest households due to a lack of savings or access to bank loans. Second, because of a higher break-even point. Affluent American households would be able to save on fuel thanks to the CAFE standards: fuel savings would quickly compensate for the extra cost of the purchase. Poor households that are already limiting their trips to save on fuel using an inefficient vehicle will not be able to reach — for lack of income — the break-even distance for which the saved fuel compensates the additional purchase cost of a new car. These households are thus vulnerable to any subsequent increase in fuel price or tax. They suffer from reduced mobility leading to fewer opportunities in employment, leisure, and education Davis and Knittel (2016); Levinson (2019). This deprivation is difficult to capture in the data, that is why CAFE appears to be progressive when one considers new vehicle purchases. Nevertheless, the subsequent increase in second-hand vehicle prices a few years later, mainly affects low-income households making CAFE regressive (Jacobsen, 2013).

Similarly, the new energy regulations prevent the construction or rental of poorly insulated housing (*"passoires énergétiques"* in French) which often house low-income households. Such regulations are effective in reducing energy consumption (Kotchen, 2017) but at the cost of increased average rents and housing prices. In response, the lowest income quintile reduces the surface area of their dwellings by 4-6%, compared to only 0.6-1.6% for the higher quintile (Bruegge et al., 2019).

However, command-and-control instruments have the benefit of cancelling a part of the decision-making of households, thus fighting consumer myopia. Consumers tend to misjudge and underestimate future energy savings and refuse to pay the premium for energy efficiency (d'Adda et al., 2022). If this premium is low, then it might benefit all consumers, regardless of their income. By forcing the consumer to invest in an efficient appliance, the government corrects this bias and favours the least informed consumers — often the poorest households.

There is growing literature on the distributional impacts of different policy instruments, although it is still largely focused on the carbon tax, but little on the impact of a package of measures and the cross-effects of different policies in space and time. Chapters 1 and 2 assess the distributional consequences of several simultaneous measures, and study their interactions and the consequences in emissions reduction and cost distribution.

4 Indirect distributional impacts: wages, capital revenues and employment

The direct distributional effects are the most easily perceived — on the bill or at the pump — but climate policies also affect household incomes through indirect macroeconomic source-side impacts and prices through general equilibrium effects. These effects still lack strong empirical validation for most of them. This section describes the channel through which climate policies might have indirect distributional impacts.

Firms and climate policies

Firms will face increased fossil fuel costs — through direct taxation, standards or emission trading — and will either pass some costs increase on to consumers through prices or reduce their profits.[30]. Losses of profit are reflected in lower wages, lower investment, lower dividends and lower corporate tax revenues for the government.

Low-income households are the most affected by a decrease in tax revenues as social transfers — which are the redistribution of the amounts collected through taxes — represent a larger share of their income than wealthy households. However, if carbon taxation raises the general price level, low-income households may benefit from the indexation of social benefits to the price level, while wages and capital income do not.

Carbon-intensive industries tend to pay above-average wages (Antosiewicz et al., 2022). Mitigation policies might affect the wage level in these industries, it would then affect middle and high incomes downwards: the effects might be expected to be progressive. Conversely, if the carbon-intensive sectors are also low-skilled labour intensive, then the carbon price will lower the wages of the less skilled (Fullerton and Monti, 2013).

There is no consensus on the evolution of capital income, with three diverging effects partially offsetting each other. Firstly, mitigation policy might limit profit, meaning firms have less capacity to invest in green technologies or energy efficiency in the long term, for example, in R&D (hence the specific support policies). A drop in R&D in the short term may imply greater damage and costs in the future — burdening the poorest — or jeopardise the firm future performances when faced with increasing energy costs. Therefore, reduced profits mean lower dividends and capital income, thus affecting mostly the richest households. Secondly, capital-intensive goods are on average more carbon-intensive than other goods (Dissou and Siddiqui, 2014): emission reduction policies curb the demand for capital — and thus its yield. Thirdly, energy-efficiency or abatement technologies require significant investments and increased recourse to capital (Metcalf, 2019; Fullerton, 2008).

More anecdotally, a proactive policy to reduce air pollution in a given area may have unexpectedly unequal effects. Land and housing would become more attractive, and thus more expensive, benefiting, in the end, landlords over tenants (Fullerton, 2008).

Policymakers regularly justify the limitation or delays of climate action by the need to protect the competitiveness of national companies and, ultimately, jobs. D. Trump thus declared, with regard to the Paris climate agreement, that "This agreement is less about the climate than it is about [the fact] that other countries are getting a financial advantage at the expense of the United States". This is classic climate action delay (Lamb et al., 20ed).

For 20 years, most economic studies have concluded that environmental regulations and carbon taxes have a negative but small impact on competitiveness (Jaffe et al., 1995; Dechezleprêtre and Sato, 2017). None of these policies has significantly contributed to the destruction of jobs or has significantly encouraged the relocation of companies (Martin et al., 2014). However, these estimates are aggregated at the macro level and can hide a large disparity. There has been, however, some carbon leakage, with foreign emissions remaining constant and domestic emissions falling, but no massive relocation

[30]See the literature on estimating the carbon tax pass-through, Li et al. (2014); Ganapati et al. (2020).

of jobs. The slight drop in profits is partially compensated by "clean" innovation — encouraged by low-carbon regulations — which reduce resource use and firms costs (Calel and Dechezlepretre, 2016). It should be noted, however, that if the impact on competitiveness is weak, it is also because the sectors most at risk are also those that benefit from exceptions and adjustments (Venmans et al., 2020), thus studies might be biased by the endogeneity of environmental regulations (Dechezleprêtre and Sato, 2017).

The energy transition contributes to creating more jobs than it destroys (Barker et al., 2016; Quirion, 2013; Callonnec et al., 2013). The "green" jobs created are mainly technical and managerial positions (Marin and Vona, 2019), but manual workers benefit from a more significant rise in salary than others (+8%). The emblematic carbon-intensive industries such as coal mines are very concentrated, and their closure have important consequences for local employment (see Haywood et al. (2021) for a case study on miners in Germany). This concentration of activities also concentrates discontent, which can amplify opposition to climate policies. The lobbying of carbon-intensive industries uses this argument to negotiate exemptions — as in the case of the European carbon market EU-ETS. Dechezleprêtre and Sato (2017) also hypothesises that companies, by playing on the complexity of production costs (of which the environmental component is only a part) blame unpopular relocations and job losses on government climate policies. Firms demand subsidies rather than binding targets and divert part of public spending, creating rents for themselves, to the detriment of social transfers (Dechezleprêtre and Sato, 2017).

The indirect effects of climate policies on household income are ambiguous. The literature suggests that it is essential to consider both source and use-side effects — direct and indirect — simultaneously to get a complete picture of the distributional effects of environmental measures. (Goulder et al., 2019).[31]

Green technical change

The price of carbon drives innovation in clean sectors by discouraging investments in dirty sectors (Acemoglu et al., 2012).[32] The empirical literature is fairly unanimous on the positive impact of energy prices on energy-savings innovations, at national level (Popp, 2002) and at firm-level (Aghion et al., 2016; Noailly and Smeets, 2015). More directly policy-related, (Calel and Dechezlepretre, 2016) shows that the European ETS has a small but positive impact on patenting in energy-savings innovation. However, as with any technical change, the impact of green technical change on equity and employment is not clear. We rapidly present some evidence of the relationship between innovation and inequalities.

Two channels link innovation to inequality: the reduction of employment and wage, and the creation of a gap between skilled and low-skilled workers. First, innovation,

[31] See appendix 2.C of Chapter 2 for a full review of the literature on micro-macro modelling to encompass both source and use side effects.

[32] We refer to Popp (2019) and Jaffe et al. (2005) for more complete reviews on the subject

especially through automation and robotisation, has a negative impact on employment and wages in the US (Acemoglu et al., 2020; Acemoglu and Restrepo, 2020a). Second, technical change appears to be skill-biased overall, increasing the demand for the most skilled workers (Acemoglu and Autor, 2011; Katz and Autor, 1999). Most studies forecast an increase in employment following the energy transition. We will then focus on the skill-biased effects because green jobs are likely to be skilled.

Education can compensate for the bias of technical change by increasing the supply of high-skilled workers in the economy. It has been the case in the first half of the 20th century. However, there has been an increase in the wage premium since the 1970s, following a slowdown in higher education in the US (Goldin and Katz, 2007). Empirically, low-wage growth leads to higher automation (Dechezleprêtre et al., 2019). Low-skills intensive sectors are sensitive to low-wages increase, which increases the demand for automation. New tasks, irrespective of technical change, can reduce the wages of some of the workers, and have contributed to the rise in wage inequalities in the United States (Acemoglu and Restrepo, 2020b). The automation of routine tasks, notably via the new information technologies in the 2000s, has reallocated low-skilled workers to services and even less skill-intensive tasks (Autor and Dorn, 2013). There has been a polarisation of wages and a decline in the lowest wages, except in services where low-skilled workers are difficult to replace. Technical change is therefore also routine-biased technological change (Goos et al., 2014).

Innovation does not appear to raise the level of inequality on average but does favour top 1% incomes (Aghion et al., 2019). An improvement in productivity improves the employment of both low and high-skilled workers. Indirect effects qualify these increases: inflows to the city increase rents, and property values for home-owners, but the lower mobility of low-skilled workers prevent too much competition on wages(Hornbeck and Moretti, 2018). Note that the consequences for wages and rents spread beyond the city where the technical change has taken place (Green et al., 2019; Hornbeck and Moretti, 2018).

In the other direction, it is interesting to look at the co-determinants of technical change and inequality. In a classic framework, wages and innovation are both negatively affected by an increase in supply of labour. However, it might be more complex. Take the impacts of immigration: it increases labour supply but its effects on patenting and wages is not clear as immigration can lead to more (Andersson et al., 2020) or less innovation (Danzer et al., 2020). Effects on local wages are supposedly negative, but can be compensated by the reallocation of native workers to other sectors (more intensive in communication tasks), preventing the fall in wages (Peri and Sparber, 2009). Labour market conditions affect technology adoptions and wages inequality, whether it is the regulatory context (Acemoglu and Finkelstein, 2008; Dechezleprêtre et al., 2019) or the ageing dynamics of workers in the sector (Acemoglu and Restrepo, 2022). There are multiple conditions affecting innovation and technology adoption. The effects of innovation on wages and employment depend on the type of technical change being discussed: process innovation, product innovation or automation. Overall, it makes the distributional effects of innovation difficult to anticipate.

Chapter 2 of this thesis develops a micro-macro methodology for modelling the direct and indirect effects of the French low-carbon strategy in the short and medium term, confirming that macro effects only partially mitigate the use-side inequalities of low-carbon policies. Chapter 3 studies more specifically the sectoral impact of the carbon price on labour-saving technical change.

5 Compensating distributional effects

The previous section shows that climate policies have heterogeneous impacts on households and that it is often the poorest households who are at a disadvantage, no matter the instruments implemented. Carefully designing policies can reduce these impacts. For instance, implementing an income threshold for subsidies ensure it benefits low-income households. As for carbon taxes, the question is: should policymakers give carbon tax exemptions to households or firms if the consequences are likely to be unfair?

If we consider that the policy-induced inequalities reflect pre-existing inequalities of income or consumption, then it is reasonable to conclude that the fairness of the climate policy must be addressed with a separate instrument. This is a less conventional application of Tinbergen's rule already mentioned (Tinbergen, 1952). From this point of view, climate policy instruments (taxes, standards or quotas) meet the effectiveness objective, i.e. reducing emissions. The compensation of inequalities is another objective which should therefore benefit from a separate instrument. Chapter 1 shows that the polluter-pays incentive to pollute less, supplemented by compensation, is more effective in reducing emissions than, for example, a carbon tax exemption.

Compensation instruments help limit inequalities and win popular support for green measures (Carattini et al., 2019) (see section 6). Most of these measures are financed by the revenues of a carbon tax or the auction of emissions allowances and are thus budget neutral.[33]

We can divide compensation instruments into three categories: support for low-carbon investments, direct cash transfers and indirect transfers through improvements of the current tax system. The literature does not converge on a single optimal use of carbon tax revenues but agrees that increasing existing benefits is likely not the best use of revenues. Indeed, a large number of households never claim the benefits to which they are entitled (Gonzalez and Nauze-Fichet, 2020) and there is no guarantee that the eligibility of households for these benefits covers the "losers" of climate policies (Vogt-Schilb et al., 2019). As in the case of mitigation policies, the second-best option is probably to combine them: a lump-sum transfer and a labour tax cut (Jacobs and de Mooij, 2015). We review these two options.

[33]To ensure a balanced budget, the use of carbon tax revenues cannot be subject to an *a priori* objective (e.g. pre-tax levels of inequality). The use of these revenues must also take into account that the carbon tax base is bound to decrease over time, and that the volume collected may decrease if not offset by an increase in the tax rate.

5.1 Direct Lump-sum transfers

The most straightforward redistribution mechanism of the carbon tax revenues is a direct lump-sum transfer to all households.[34] If the rebate is made on an equal per capita basis, it tends to more than compensate low-income households. Indeed, low-income households dedicate a larger share of their income to carbon, but the equal per capita rebate also accounts for a larger share of their income. Conversely, the equal per capita rebate weighs little in the income of the richest households and does not offset their carbon tax bill — although carbon tax represents a smaller share of their income is substantially larger in volume than the low-income one.

Overall, most studies find that recycling revenues in the form of lump-sum transfer makes the carbon tax progressive, and that it shields the most vulnerable against energy price increases (Klenert et al., 2018b,a; Budolfson et al., 2021; Carattini et al., 2019). It is worth noting that the progressivity of the net tax with a lump-sum transfer does not rely on any hypothesis. Income inequality is not a requirement for the carbon tax to be fair as a more equal income distribution would imply the carbon tax is already progressive or neutral *prior* to any recycling.

However, lump-sum transfers have higher efficiency costs than other uses of the revenues: they disincentive work and increase the general price level. van der Ploeg et al. (2022) estimates that a lump-sum transfer ultimately leaves 70% of households worse off, compared to only 30% with a labour tax cut (see below). Another drawback of lump-sum transfers, is that they blindly compensate all households: rural and urban, low- and high-emitting households, without distinguishing between basic needs or luxury consumption.

A common idea in the literature is to better target lump-sum transfers on the most vulnerable households. It includes low-income and rural households. Rural households are more affected by a carbon tax than urban households because they are more dependent on private cars with little to no public transport alternatives, while jobs are clustered in urban centres; they tend to have larger and less well-insulated individual homes (Bureau et al., 2019). This leads to two other debates. The first is how much of the tax revenue should be recycled towards households, and how much should be spent on other uses, such as thermal renovation subsidies (Bourgeois et al., 2021) or green investment (Feindt et al., 2021). The second is how much an incentive to relocate should the carbon tax be. There is a trade-off between revitalising rural areas and reducing home-to-work distances to save on fuel.

Chapters 1 and 2 simulate different levels of carbon taxes and various recycling mechanisms of the carbon tax revenues based on more or less narrowly targeted lump-sum transfers. They assess the impact on the most vulnerable through different criteria.

[34]It may or may not be adjusted to the household size with equivalence scale.

5.2 Looking for the double dividend

The recycling of carbon tax revenues as cash lump-sum transfers to households is sub-optimal (Goulder, 1995). Carbon tax revenues can be used to improve the current tax system by reducing distortive — taxes that affect the proper functioning of the market — such as labour taxes that disincentives work. The goal is to reduce unemployment and thus increase welfare. It would generate economic benefits, supplementing the environmental benefit of reducing emissions, it is a so-called *'double dividend'* (Chiroleu-Assouline, 2001; Pearce, 1991; Goulder, 1995). Unlike most taxes, the Pigouvian tax effectiveness lies entirely in the price signal (although we study in Chapter 1 the influence of carbon tax revenues on the reduction in emissions). The levied revenues can be then used to any purpose. It then makes sense to improve welfare, especially since most people are not convinced of the effectiveness of the tax to reduce emissions (Carattini et al., 2017a). Cutting distortive labour taxes would then constitute a "no-regret" option improving welfare independently of environmental outcomes.

At the heart of the use of carbon tax revenues is the equity-efficiency trade-off. Cutting labour tax cut reduces efficiency costs compared to a lump-sum transfer by limiting the interactions between taxes (Goulder et al., 2019; Williams et al., 2015). The mechanism is as follows: a carbon tax increases production costs, which is passed on to the prices of consumer goods. Real wages mechanically decrease: the incentive to work decreases, thus so does the labour supply, the detrimental effect of income taxes on employment is increased, generating additional costs.

The labour tax cut can be designed to lower taxes on low-income workers and thus improve the progressivity of labour taxation and offset the potential regressive impacts of carbon taxation (Chiroleu-Assouline and Fodha, 2011). Theoretically, a strong double dividend — an increase in welfare — is achievable in many situations, even in the presence of labour market failures: e.g. unemployment (Hafstead and Williams, 2018), employment heterogeneity of low-skilled workers (Aubert and Chiroleu-Assouline, 2019), and more generally heterogeneity (Jacobs and de Mooij, 2015; Chiroleu-Assouline and Fodha, 2011) The literature has established a number of conditions for a double dividend to emerge (Bovenberg and Goulder, 2002; Goulder, 2013). .[35]

Simulations in computable general equilibrium models offer a more contrasted picture: Freire-González (2018) carried out a very comprehensive literature review and meta-analysis of computable general equilibrium modelling, and finds that half of the simulations studied highlight a double dividend[36] and half do not. Overall, general equilibrium studies show a trade-off between equity and cost-efficiency: a labour tax cut maximises efficiency, while equity (and the shielding of the poorest households) is favoured under a lump-sum transfer even if there is no double dividend (Fremstad and Paul, 2019; Williams et al., 2015). Some other limited studies show that capital tax cuts perform better than labour tax cuts (Jorgenson et al., 2013). However, even if capital

[35] A number of theoretical studies show that under certain conditions there is no double dividend, e.g. Fullerton and Metcalf (1997) and Babiker et al. (2003).

[36] For instance, Goulder et al. (2019) finds a double dividend for a carbon tax in the US, or Labandeira et al. (2009) in Spain.

tax cuts are supposed to spur the economy, the "trickle-down" narratives would hardly be accepted by the population (Dechezleprêtre et al., 2022).

There are two outstanding examples of the use of carbon tax revenues to lower taxes on labour. The first is the example of Sweden, which introduced a carbon tax very early on in the 1990s. The particularity of the Swedish reform is that it was not conceived as a stand-alone environmental reform but as an overhaul of the tax system. Sweden has largely reduced its emissions thanks to this carbon tax (Andersson, 2019) although it is difficult to highlight a double dividend specific to the carbon tax revenues recycling in this case. The Canadian province of British Columbia implemented a carbon tax in 2008. It is a revenue neutral stand-alone: 100% of the revenues are used for tax credits, both for households — targeting the low-income — and corporate tax cuts. As in other countries, the tax was seen as inefficient and unfair, particularly for rural communities (Beck et al., 2016). Ex-post studies show large reductions in emissions from fuels or certain sectors (see Murray and Rivers (2015) for an overview of the literature pre-2015) but no significant effect on aggregate emissions could be found (Pretis, 2022)— which does not mean that it did not have any — but this may be because of its low initial level (about 24$/tCO_2$ in 2015). However, the tax has become more popular over time, showing the effectiveness of recycling (and information) for social acceptability (see next section). The recycling mechanism has limited the burden of the tax for low-income and rural households (Beck et al., 2016). The French government has chosen to use the revenues from its carbon tax in 2013 to reduce corporate tax (CICE). This reform, whose first evaluation does not show any significant effect on employment (Carbonnier et al., 2018)., was moreover not targeted on low wages and not designed to specifically offset the effects of the carbon tax.

6 Social acceptability and political feasibility

As previously underlined, carbon taxes are one of the most effective instruments for reducing emissions because they allow for flexibility and do not impose mitigation technologies (unlike subsidies or some regulations). They also are simple to manage and raise revenues. And yet, only a small number of carbon taxes have been implemented worldwide. The World Bank (Bank, 2021) lists 64 carbon price mechanisms across the globe, including Emissions trading systems (ETS), in 2021. They cover 15.5% of global emissions. Note that only 15.1% of emissions were covered in 2020. The increase is mainly due to the launch of China ETS in February 2021, and to a small extent, to the launch of UK ETS, following its departure from the EU. The countries that have adopted significant carbon prices above US$20 per ton[37] are European countries[38] and Canada and its provinces[39]. In addition, there are some countries with lower carbon

[37]This is an arbitrary threshold to restrict the list to the more significant carbon taxes, see Bank (2021) for the full list.

[38]Denmark, Finland, France, Iceland, Ireland, Lichtenstein, Luxembourg, the Netherlands, Norway, Portugal, Slovenia, Sweden, Switzerland, United Kingdom.

[39]Different systems coexist in Canada, a federal carbon price and systems by province: New Brunswick, Newfoundland and Labrador, Prince Edward Island, Northwest territories.

prices in South and Central America [40], in Europe[41], Singapore and South Africa. The ETS covers some of the countries that already have a carbon price in place but extends to other geographical areas: the European Union, another ETS in Germany, Switzerland, the UK, Canada[42], and New Zealand, as well as other provinces and countries with lower market carbon prices: Chinese and Japanese provinces and cities, the Republic of Korea, California and Massachusetts US states, and Kazakhstan.

Overall, the number of countries which have implemented a carbon price is low. Two barriers can easily be identified: the opposition from economic interest groups (lobbying)[43] and popular opposition. The remainder of the section focuses on the latter as this dissertation studies the equity dimension of climate policies, which are hardly a concern for economic interest groups.

The main concerns and barriers to adoption are common to all environmental policies (Dechezleprêtre et al., 2022; Carattini et al., 2017b): i) anticipating low effectiveness of the policy in reducing emissions, ii) judging the policy to place an unfair burden on the most vulnerable households, iii) expecting high personal cost and large impacts on one's household.

Two concerns are more specific to carbon taxes: iv) that the government is only using the carbon tax to disguise a new tax, thus increasing its revenues without real environmental concerns[44](Baranzini et al., 2017), v) and the damages it could create to the economy (in terms of employment, competitiveness, and trade).[45] Acceptability also depends on the level of the tax. For example, a low carbon tax, even if unfair, rarely starts public protests. In the *Gilets Jaunes* case, it was the rise in the price of oil that started the protest. The increase in the price of gasoline prompted investigation into the price components and shed lights on the recent increase in carbon pricing for gasoline (CCE) (Carattini et al., 2017a).

Let us note that the vast majority of the literature studying the social acceptability of climate policies focuses on carbon tax in Western (Fairbrother, 2022). Even though some Global South countries have had similar protests. In 2012, the Nigerian government cancelled gasoline subsidies — officially for environmental reasons, but more likely to

[40] Argentina, Chile, Colombia, Mexico.

[41] Poland, Latvia, Ukraine, Spain

[42] And some of its provinces: Alberta, British Columbian, Quebec, Nov Scotia.

[43] See Oates and Portney (2003) for a presentation of the mechanisms; Brulle (2018) for a census of lobbying expenses of industries on the subject of climate change; and Bonneuil et al. (2021) a case study on Total lobbying and strategy to discredit climate change science from 1971.

[44] Note that this was the case in France, where the Contribution Climat Energie (CCE) was justified by the need to finance corporate tax cut (Crédits Impôts Compétitivité Emplois, CICE) in 2013, whereas the CICE is only a possibility to use the revenue from the CCE, a green tax whose primary objective is the reduction of emissions (Chiroleu-Assouline, 2015)

[45] Carattini et al. (2018) groups opposition to carbon taxes into 5 categories: First, the impacts of the taxes are directly perceptible. Second, carbon taxes are regressive, or at least perceived to be so (Sterner, 2012). Third, the job killing argument, and the impacts on competitiveness. Fourth, the inefficiencies of taxes, especially in a context where the poorest are dependent on fuel, and therefore have a rather inelastic consumption. Fifth, citizens think that the carbon tax is just a pretext for the state to raise additional taxes

fund other budgets — the price of gasoline doubled overnight (from 65 Naira to 141) triggering a similar doubling in prices for bus tickets, and fruits and vegetables. The poorest households were the most affected. The subsidy was partially reintroduced after 15 days of strike and 11 deaths during the protests.

Dechezleprêtre et al. (2022) analyses the result of an important multi-country survey about perceptions and attitudes on climate change and climate change policies. Popular support depends on the policy: subsidies for low-carbon technologies and green public investment are the most popular measures. Regulations such as bans on polluting vehicles in dense areas are also very popular. Conversely, carbon taxes gather low support. However, the use of revenues is key: a carbon tax with transparent use of revenues is more popular.[46]. Earmarking revenues for environmental spending is very popular as it is seen as a way to compensate for the supposed inefficiency of the carbon tax[47]. Lump-sum transfers directed to the poorest or most constrained households are also widely supported. Finally, lump-sum transfers on an equal per capita basis and cuts in labour taxes do not improve support, in this latter case, maybe because the double dividend is not very intuitive.

One of the key points is that people underestimate what they will earn from the recycling of carbon tax revenues (Douenne and Fabre, 2022): about 20% of households in high-income countries think that they will not benefit from the implementation of a tax with cash transfer (Dechezleprêtre et al., 2022). The middle-income countries are more optimistic in that regard. It is as much an anticipation problem as a trust issue between citizens and their government. This obviously has a negative impact on acceptability (Stiglitz, 2019).

Overall, households prefer subsidies and regulations to taxes (Drews and van den Bergh, 2016), despite the subsidies and regulations also having distributional impacts: these are less directly perceived on the bill (see section 3).

It appears that climate policy design matters hugely in the acceptability of climate policies (Ewald et al., 2022; Carattini et al., 2018; Klenert et al., 2018a). The use of the revenues in the case of a carbon tax is key. Pedagogy, transparency and information about climate change in general and climate change policies always increase public support, sometimes dramatically as in the case of a carbon tax (Dechezleprêtre et al., 2022). Counter-intuitively, even if higher carbon taxes are less likely to be accepted, it is important that the ambition of the climate policy is adequate to the level of the climate crisis. It might debunk the belief that climate policies have less to do with climate and more with financing the government budget (Chiroleu-Assouline, 2015). Chiroleu-Assouline (2022) provides an overview of the envisaged solutions to implement a fair carbon price. It focuses on French specificities, among them the concern about the contribution of the richest households. It shows that a carbon price recycled largely towards the poorest or a tax at the European borders could be acceptable to the population.

[46] See Ewald et al. (2022); Carattini et al. (2017b) for a full literature review.

[47] Information on the real effectiveness of the carbon tax decreases support for this use of revenue compared to other uses (Carattini et al., 2017a).

This dissertation focuses on acceptability and feasibility from an individual perspective: people are more likely to vote for a policy that they perceive as fair and that benefits them. Chapters 1 and 2 propose several recycling mechanisms of the carbon tax revenues. They study how recycling mechanisms may favour the most vulnerable, and how they interact with emissions targets and other policy tools.

7 This dissertation

This dissertation collects 4 research papers at different publication stages. They provide answers to the following question: How are the consequences of climate change mitigation policies distributed among households and workers? The objective of this dissertation is to anticipate the distributional consequences of climate policies in order to maximise social acceptability and to favour a fair transition.

We answer the main research question from two angles: the distributional use-side effects of climate change mitigation policies (Chapters 1 and 2) and the source-side effects on income and employment (Chapters 3 and 4). We show that a carbon tax can be fair and reduce CO_{2eq} emissions if combined with well-targeted subsidies and redistribution (Chapters 1 and 2). Carbon pricing may also spur low-carbon and energy-efficient technologies to reduce emissions of the production but may have source-side impacts on wages and employment. We find empirical evidence of price-induced labour-saving and capital-saving innovation (Chapter 3). We find that labour and capital cost induce respectively energy-using and energy-saving innovations, but we find no energy-saving technical change induced by energy prices at the sectoral level (*preliminary results*, Chapter 3). However, we find that, under the condition of a case-study in the transport sector, carbon pricing and subsidies effectively incentivise firms to invest in low-carbon technologies (Chapter 4). In all chapters, we show that all mitigation policies face trade-off between their multiple objectives: between the reduction in emissions due to carbon pricing and the fairness of the revenues recycling (Chapter 1); between emissions reduction, vertical and horizontal inequalities (Chapter 2); between energy-saving and labour-saving innovations (Chapter 3); and between less expensive or less carbon-intensive technologies (Chapter 4).

7.1 Contributions

The first chapter, *Can a carbon tax increase emissions? Backfire of carbon tax recycling and distributional impacts*, assesses how households reduce or increase their emissions following the introduction of a carbon tax and revenue recycling in the form of a direct cash transfer. We estimate that a carbon tax of €158/ton of carbon and full recycling of the revenue from this tax through an equal per capita rebate would decrease households' total carbon footprint by 5.9% and by 7.4% if the richest 20% are excluded from the recycling. There is a backfire effect for almost a quarter of households that increase their emissions following the introduction of the tax and the recycling mechanism. Recycling ensures that the carbon tax is progressive and reduces the burden on the poorest. The first contribution of this chapter is to study the income effect of the recycling of carbon tax revenues to households — which can go as far as cancelling out the price effect, thus creating a backfire in emissions — a topic that has been little studied until now. We show that the recycling does not completely cancel out the emission reduction due to the carbon tax. Partial recycling of revenues, excluding the richest and focusing on low-income households, would further reduce emissions and increase the progressivity of the tax. The second contribution of the chapter is to provide disaggregated long-term elasticities for French Households. We estimate price and income elasticities for 40 classes of French households for 14 consumer goods using 30 years of consumer expenditures surveys. The final contribution of this chapter is to highlight the great heterogeneity in the behavioural reactions of households. We show that income level plays a key role in the ability of households to reduce their emissions in the face of a carbon tax and the use of the additional income from recycling. We complement studies pointing to the role of horizontal inequalities by showing strong territorial — urban-rural — and generational disparities in emissions reduction.

The second chapter, *Is a fair energy transition possible? Evidence from the French Low-Carbon Strategy*, assesses the distributional impacts of a package of measures which is part of the trajectory to reach carbon neutrality in France by 2050. We simulate these measures from 2025 to 2035 using the MATISSE microsimulation model and the IMACLIM-3ME macroeconomic model linked together. These measures include an upward trajectory of the carbon price, and subsidies for thermal renovations and electric vehicles. The first contribution is the assessment of the distributional impacts of simultaneous policy measures on both vertical dimensions — on income — and horizontal dimensions – on other criteria, especially urban *vs.* rural. We find that this policy package is regressive if there is no recycling of carbon tax revenues. In other words, source-side effects and subsidies to clean technologies (renovation and electric vehicles) do not offset the regressivity of the carbon tax in the short run. However, subsidies are complementary to recycling and decrease emissions in the medium term. The second contribution is the simulation of various design of the policies. We conclude that the distribution of technologies among households is essential to maximise the reduction of emissions and limit territorial inequalities between urban and rural areas. Selecting beneficiaries among high energy consumers has more impact than increasing the volume of poorly targeted subsidies. Conversely, targeting the recycling of carbon tax revenues on low-income households makes the tax progressive but does not limit urban vs rural inequalities, while targeting rural households leave the poorest households vulnerable. We conclude that the design of the policy can strongly influence their distributional impacts and that a mix of policies can maximise emissions reduction and limit inequalities on several dimensions.

The third chapter, *Disentangling the directions of technical change: a new growth accounting method*, provides a technical change and growth accounting framework. This chapter has a methodological contribution, the proposed framework disentangles between factor substitution and specific factor-saving technical change in the production. It can be used at both macroeconomic and industry levels. Technical change is represented by the convex envelope of factor-saving deformations of a single Leontief production function. The main contribution lies in the application of this model to US and European capital and labour use at the sectoral level. We use the KLEMS databases between 1970 and 2019 to study the bias of sectoral technical change. We find that most industries are net-capital-savings with a trend towards net labour-saving. We are able to link the variation of the net labour-saving trend to specific innovations or economic events. The third contribution is to test the Hicks hypothesis of technical progress seeking to save on one specific input when its price increases relative to other factors. We show that technical progress is labour-saving when wages increase, thus partially validating the hypothesis. A fourth contribution is to forecast the evolution of factor shares at the sectoral level at least as well as a Cobb-Douglas function or a CES function (constant elasticity of substitution). We finally extend the framework to 5 inputs including energy, and present preliminary results. We find that most industries are energy-saving; however we find no evidence that energy prices spur energy-saving innovations, while the cost of labour and capital do.

The fourth and final chapter, *Economic and environmental performances of natural gas for heavy trucks: A case study on the French automotive industry supply chain*, studies the integration of natural gas trucks into a firm's supply chain. Natural gas vehicles are a green technology that is theoretically environmentally friendly but could backfire in terms of emissions. The chapter constitutes a case-study of the previous chapter, it considers the firm decision-making process and the specific challenges it faces in adopting an innovation. We use the firm spatial data on volumes and journey per route to map the truck potential natural gas refuelling stops and the cost to switch each route to natural gas. Our first contribution is to study the transition period during which a company would switch from diesel vehicles to fossil natural gas or biogas vehicles. This chapter determines whether this technology is profitable under several scenarios combining the evolution of diesel prices and the volume of investment (in number of trucks purchased). We find that in the current state of the natural gas refuelling network, trucks make significant detours to reach refuelling stations (+6.21% in distance on average). It means that natural gas trucks increase the emissions of the journey above the level of diesel by 3 to 13%. A 100% biogas fuel reduces trip emissions by 76% compared to diesel and a 30% share of biogas is a necessary condition for natural gas trucks to reduce emissions. Relative pre-tax prices of gas and diesel and the cost of purchasing trucks are key parameters for the adoption of this technology. Well-designed subsidies and taxes can accelerate the adoption of this technology, purchase subsidies for the trucks might incentivise small firms to adopt it, and carbon taxes based on the life-cycle emissions of the fuel might favour biogas over fossil natural gas. In parallel, specific policies should develop French biogas production to fuel the adoption. In conclusion, real-life conditions can threaten the adoption of a carbon-saving technology and even offset the reduction in emissions.

7.2 Methodologies

In this dissertation, we use multiple methods to distinguish more clearly the effects of mitigation policies on inequalities. We try to illustrate why multiple approaches are important, then present the methodology used in each chapter.

To quote the provocative 'streetlight effect', economists are often pictured as drunk people looking under a lamppost for a watch they have lost on the other side of the street. Because that's where the light is. In other words, economists are seen as using models that can only give inadequate answers.

A more appropriate metaphor would be a House of Mirrors, plunged into the darkness where any light is reflected and deflected. This metaphor allows us to understand the contribution of the different methods used in the economic field. Global lighting reveals the watch we are looking for, but also all its reflections, which are difficult to differentiate from each other — there is now too much information hiding the answer in plain sight. A more concentrated beam makes the search more difficult but reduces the chance of seizing a mere reflection of what we are looking for — we better know where to investigate beforehand. If we are looking for a smart watch, then we know it is there and even its location, but without light we cannot figure out the way to get it. We may recognise here more or less parsimonious models, say a computable general equilibrium model, an applied theoretical model looking for causal inference, and finally a big data model (or a random control trial experiment). They all allow for a different angle on the question at hand. Economics is not Physics and does not aim at providing eternal truth but rather to constitute a converging body of evidence — *un faisceau d'arguments convergents* — to answer a question.

The first chapter uses microsimulation, the second chapter links a microsimulation and a macroeconomic models. The third chapter develops an accounting framework that we apply to sectoral data and the fourth chapter is a case-study on firm data.

Chapter 1 develops a detailed behavioural response model of households to a carbon tax and the revenue recycling to households. We use consumer survey data from 1979 to estimate price and income elasticities for 14 consumer goods and 40 household classes, making it the most accurate study in the French literature. The 40 household classes are the intersection of the 10 income deciles and 4 groups of households with a similar income structure and a similar share of pre-committed expenditures, thus representing their adaptability to price changes. We use these elasticities in a microsimulation model that simulates, on the French consumer expenditures survey (Budget des Familles, INSEE), the effects of the price signal of the tax on emissions and the opposite income effect of the lump-sum transfer. We simulate the aggregate reduction of emissions for different levels of carbon tax and more or less narrowly targeted recycling mechanisms of the carbon tax revenues. We test the impact of heterogeneity of preferences — expressed via the elasticities — in the reduction of emissions.

Bourguignon and Landais (2022) is a newly released note of the Conseil d'Analyse économique (French Council of Economic Analysis) on the use and generalisation of microsimulation models in France. The authors' recommendations match so strongly the work in the first chapter of this dissertation that we use it to showcase the contributions of our work. The note identifies several key points. First, improving the granularity of the data by using exhaustive administrative data helps representing both vertical heterogeneity between income deciles and horizontal heterogeneity within these deciles (e.g. territorial differences). Second, behavioural models — unlike static models — is needed to assess the avoidance of certain taxes as is the case for a carbon tax.[48] Third, generalise exchanges between modellers to develop the practice, particularly to reconcile microsimulation models with macroeconomic visions, which leads us to the second chapter.

Chapter 2 builds on the microsimulation of the first chapter. It adds the adoption of low-carbon technologies for households and links the microsimulation with a macroeconomic model resulting from the collaboration between several teams of modellers (ThreeME, IMACLIM and MATISSE model development). We develop an iterative macro-micro linkage to provide the most accurate representation of the low-carbon transition of the economy.[49] The innovative features of our models are threefold. First, we use the behavioural microsimulation model of the previous chapter. Second, we explicitly model the distribution of low-carbon technology among households. We simulate the impacts of an electric car or a thermal renovation on households budgets: the energy consumption decreases (or switch from gasoline to electricity), domestic fossil fuel consumption is switched to electricity in case of a renovation reaching a high class "A" EPD (Energy performance diagnostic), rents and rental wages increase to cover for renovation costs, owner-occupiers pays interest on the loans of the investment. Third, we ensure consistency of the macro and micro views of the economy throughout the simulations with the reweighting of households (Agénor et al., 2004). We use this coupled model to simulate five packages of policies at three short and medium-term horizons (2025, 2030 and 2035) to compare their distributional consequences and the reduction in direct emissions. Comparing packages that differ in one policy allow to pinpoint the impacts of a specific policy.

Chapters 3 develop a new growth accounting method to disaggregate the directions of technical change. These chapters build a representation of technical change by deforming Leontief production functions in factor-saving directions. We apply this framework to sectoral data to distinguish between substitution and technical change as in Jin and Jorgenson (2010); Young (2013); Herrendorf et al. (2015) following the pioneer work of Solow (1957). We use European and US time series of capital, labour, energy, material and services inputs by industries from the KLEMS databases (Stehrer, 2021; Timmer et al., 2007). We use instrumental variable methods to compare the estimations with randomly generated data, which allows us to isolate significant price

[48] Although, including behavioural responses increase uncertainty and limit the transparency of the model to the general public.

[49] The coupling of macro-micro models can take forms - top-down, fully-integrated or iterative soft-link - in climate models (see Chapter 2, appendix C) for more details.

effects on technical change direction. We use basic machine learning practices to test the ability of our model to predict changes in factor shares.

Chapter 4 complements the analysis in Chapter 3 on the links between energy-saving technical progress and employment. It is a microsimulation on a specific case study: truck transport of goods between plants in France, using Renault car manufacturing supply chain data. The interest lies in the high granularity of the data and its direct provenance from producers. The case study in itself offerh few conclusions to generalise but allows the identification of factors of variability in the results that would escape a larger study: the impact of the total travel distance, including detours, to a refuelling station and the purchase of new vehicles. This applied chapter qualifies the more general conclusions of the previous chapter.

List of articles from the thesis

Chapter 2: Ravigné, E., Ghersi, F., & Nadaud, F. (2022). Is a fair energy transition possible? Evidence from the French low-carbon strategy. Ecological Economics, 196, 107397. doi; 10.1016/j.ecolecon.2022.107397.

Chapter 4: Ravigné, E., & Da Costa, P. (2021). Economic and environmental performances of natural gas for heavy trucks: A case study on the French automotive industry supply chain. Energy Policy, 149, 112019. doi: 10.1016/j.enpol.2020.112019.

Main conferences and invited seminars

Chapter 1: Ravigné, E., & Nadaud, F., Can a carbon tax increase emissions? The backfire effect of carbon tax recycling

- Annual conference of the European Association of Environmental and Resource Economists (EAERE), 2022, Rimini, Italy
- Public Economic Theory conference (PET), 2022, Marseille, France
- Journées de Micro-économie appliquée (JMA), 2022, Rennes, France
- Berlin School of Economics workshop, 2022, Berlin, Germany
- Annual conference of the French Association of Environmental and Resource Economists (FAERE), 2021, Grenoble, France

Chapter 2: Ravigné, E., Ghersi, F., & Nadaud, F. (2022). Is a fair energy transition possible? Evidence from the French low-carbon strategy.

- Annual conference of the European Association of Environmental and Resource Economists (EAERE), 2021, Berlin, Germany (online)
- Annual conference of the French Association of Environmental and Resource Economists (FAERE), 2021, Grenoble, France (online)
- Annual conference of the International Association for Energy Economics (IAEE), 2021, Paris, France (online)
- International Energy Workshop (IEW), 2021, Freiburg, Germany (online)
- ICTA-UAB International Conference on Low-Carbon Lifestyle Change, 2020, Barcelona, Spain (online)
- EU Conference on modelling for policy support, European Commission's Competence Centre, 2019, Bruxelles, Belgium

Chapter 3: Ravigné, E., & Senouci, M. Disentangling the influence of directed technical change on factor shares: a new growth accounting method for capital and labour

- Invited Internal Seminar, RITM, Université Paris-Saclay, 2022, Sceaux, France

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CHAPTER 1

Can a carbon tax increase emissions? The backfire effect of carbon tax recycling

Joint work with Franck Nadaud (CNRS-CIRED)

> En outre, on ne peut honnêtement satisfaire les grands sans faire offense aux autres tandis que c'est possible avec le peuple : en effet la fin que poursuit le peuple est plus honnête que celle des grands, car ceux-ci veulent opprimer et ceux-là ne pas être opprimés.
>
> Nicolas Machiavel, *Le Prince*

Abstract

Recycling the revenues of a carbon tax can mitigate the distributional impacts and lowers the burden on the lowest income deciles. However, a lump-sum rebate to households induces consumption, hence emissions. In this chapter, we study the existence of a backfire effect where emissions increase above the pre-tax level because of the recycling of carbon tax revenues. We build a small theoretical model that we extend using microsimulation on French Households Budgets Surveys with long-term elasticities. We estimate that a €158/tCO_2 tax would induce a decrease of 10.9% in emissions, reduced by a uniform lump-sum rebate to a decrease of 5.9% in aggregate emissions. We conclude that the backfire effect is not a sufficient reason to prevent any compensation of the low-income households for the sake of emissions reduction. Indeed, a quarter of households increase their emissions in the face of a lump-sum rebated carbon tax, but the emissions thus emitted represent less than a tenth of the emissions of the 10th (richest) income decile. Recycling only 60% of the carbon tax revenues would reduce the backfire to decrease emissions by almost 8%. Skewing the recycling towards low-income households increases the progressivity of the tax but does not increase emissions. Our study supports the consistency between reducing inequalities and reducing emissions.

1 Introduction

Carbon pricing is a key tool to mitigate greenhouse gas emissions and climate change consequences (Pearce, 1991; Nordhaus, 1993; Stern, 2008). Carbon pricing can be implemented through a carbon tax or an emission trading system. It has proven effective in reducing greenhouse gas emissions (Green, 2021; Leroutier, 2022; Abrell et al., 2018; Andersson, 2019) but it can also be regressive in a number of countries and contexts which is a major concern for the population (Dechezleprêtre et al., 2022).[1] The use of carbon pricing revenues is therefore key to increasing the acceptability of the carbon tax, especially by redistributing all or part of these revenues to households. Recycling the revenues of the carbon tax towards households — through a cash transfer or a tax cut — is a popular option to mitigate distributive concerns. However, the compensation of households will increase consumption, hence emissions.

This chapter focuses on whether using the tax revenues to compensate households can limit the effectiveness of the carbon tax in reducing emissions — or even *backfire* and increase emissions. The intuition behind the potential perverse effect of the recycled carbon tax is simple: a carbon tax reduces emissions — to a greater or lesser extent — through the price signal. The objective of most taxes is to redistribute levied revenues through transfers or public services. But for Pigouvian taxes the redistribution is not part of the optimal design of the tax. Redistribution can then trigger an unfortunate effect: whatever the recycling, the excess revenue for households will result in more consumption and hence more emissions compared to a situation in which the tax is levied but not recycled. The reduction of emissions will therefore be lesser than expected. Emissions could even increase above pre-tax level.

Let's take a simple example and consider that all households are dependent on gasoline: their response to the carbon tax is to decrease other consumptions and maintain their gasoline consumption. Low-income households are in the paradoxical situation of energy deprivation while dedicating a large share of their income to gasoline. They will then bear a significant burden from the tax. It is only fair that most of the carbon tax collected should go to them to correct the regressivity of the tax. Low-income households thus receive a larger rebate than the carbon tax they have paid. They might resume all their consumption at the pre-tax level, and use the excess income to purchase more

[1]Meta-analyses show ambiguous results on the regressivity of the carbon tax (Flues and Thomas, 2015; Ohlendorf et al., 2020; Feindt et al., 2021). In the French case, however, Douenne (2020) and Berry (2019) show a clear regressivity. However, it is mainly the perceived regressivity that threatens the social acceptability of the tax (Carattini et al., 2017; Ewald et al., 2022).

gasoline to increase their mobility. The increase in emissions that follows might more than offset the reduction in emissions of high-income households if they have chosen to reduce low-carbon intensity consumption more than carbon-intensive consumption. In this example, there is a transfer from clean consumption of high-income households to dirty consumption of low-income households, thus creating a backfire effect.[2]

Whether or not there is a backfire stemming from the recycling of carbon pricing revenues to the household is an important question for policymakers. If a fair tax means fully cancelling out the reduction emissions with revenues recycling: then it might be best to renounce the tax or to fully redesign it.

In this chapter, we develop a microsimulation model to assess the effects of a carbon tax and a direct lump-sum recycling of the carbon tax towards households. First, we solve a compact theoretical model to illustrate how the different mechanisms allowing for a backfire effect could interact. Importantly, this model shows how heterogeneous carbon intensities and elasticities drive the backfire effect. We use past expenditure surveys to estimate the price and income elasticities by disaggregating goods and households as much as possible. We use these elasticities and the latest French Consumer Expenditures survey to calibrate the microsimulation.

We find no aggregate backfire effect. No matter how we recycle the carbon tax revenues to households, aggregate emissions decrease. We estimate that a €158/tCO_2 tax[3] would bring a decrease of 5.9% if recycled on an equal per-capita basis. The recycling offsets less than half of the carbon tax reduction in emissions (10.9%). Although there is no aggregate backfire effect, with an equal per-capita rebate about 25% of households experience individual backfire effects, i.e. increase their emissions above pre-tax levels. Recycling only part of the revenue from the carbon tax further reduces emissions and limits income effect. Targeting low-income household ensures the progressivity of the tax and compensates a large number of poor households but increases the number of low-income households experiencing individual backfire.

We find that the regressivity of the carbon tax is worsened by lower price elasticities of low and middle-income households for energy goods. Occurrence of individual backfire effects depends more on non-income dimensions — such as the income structure and pre-committed expenditures and age and location (rural, small or big city) — than on income deciles.

This chapter contributes to two main strands of literature. First, we contribute to the literature on the distributive impacts of carbon taxes. Most articles concludes

[2]This kind of perverse effect of taxation is not unique to carbon taxes. Mayeres and Proost (2001) studies a tax aimed at internalising congestion. Paradoxically, the reduction in congestion due to the tax makes car travel more attractive for some people – whom the tax discourages – because the traffic is more fluid than before the tax. There is a feedback effect of the level of externalities on the consumption of the taxed good, i.e. a perverse effect of the tax, which partly cancels out its incentives. This perverse effect stems from the heterogeneity of individuals and diverse time valuations and preferences.

[3]This level of carbon was supposed to be a milestone of carbon taxation in 2025 prior to the freeze that followed the Gilets Jaunes protests.

that recycling the carbon tax revenues, either in the form of a lump-sum transfer (Budolfson et al., 2021; Cronin et al., 2019; Fremstad and Paul, 2019; Klenert et al., 2018; Beck et al., 2015; Ekins and Dresner, 2004) or to cut labour tax (Pearce, 1991; Parry, 1995; Goulder, 1995; Aubert and Chiroleu-Assouline, 2019) makes the tax strongly progressive.[4] Although, to the best of our knowledge, there is no literature on the impact of recycling the carbon tax revenues on emissions and the potential "backfire effect".

Two fields are at the frontier of this research gap but do not answer our research question. The closest approach is that of the Environmental Engel Curves (EEC), which allow for the estimation of income elasticities of emissions (Pottier (2022) provides a survey of income elasticities of GHG emissions). Sager (2019) estimates EEC and assesses the increase in emissions due to a reduction in the Gini index representing income inequalities. The second is the study of the well-known "rebound effect" following energy-efficiency measures such as thermal renovation (see for instance Gillingham et al. (2016)). Belaïd et al. (2020) focuses on residential electricity demand and finds that the increase in emission following thermal renovation is sensitive to income. Druckman et al. (2011) coined the term "backfire" when the rebound effects exceed 100% due to economy-wide effects. An even further field studies the risk of carbon leakage due to a carbon tax and thus the potential increase in emissions (Hoel, 1991; Markusen et al., 1995; Copeland and Taylor, 2013). It is outside the scope of this chapter as we focus on households rather than on production decisions.

Second, we contribute to the literature on the estimation of elasticities. The most related article is Douenne (2020). It estimates price elasticities for transport and housing energy prices for 50 cells of households (10 income deciles and 5 sizes of urban units) to microsimulate the distributional impact of a carbon tax on fuel in France. Calvet and Marical (2011) also point out the importance of non-income dimension in the estimation of energy elasticities.[5] In contrast to these studies, we do not estimate system elasticities, which allows us to achieve a high level of disaggregation. We test the robustness implication in appendix 1.C.1. We conclude that our estimates of emissions reduction are accurate at 0.1%.

The rest of the chapter organises as follows. In section 2, we develop a theoretical framework to derive the conditions of the existence of a backfire effect with increasing heterogeneity between households. In section 2 we present the consumers' expenditures database, the microsimulation model and the estimation framework for elasticities. In

[4] In this chapter, we estimate the effect of lump-sum transfer for two reasons. The first one is political: using the carbon tax to lower labour tax would require a complete reshuffle of the tax system, which is less likely to happen than a stand-alone carbon tax and its lump-sum recycling transfer. Sweden has been an exception in that regard. It has greatly contributed to the success of their carbon tax. The second reason is technical: estimating the effect of a double dividend would require a general equilibrium model that would be difficult to calibrate, especially to capture heterogeneity in households, see for instance Rausch et al. (2011); Goulder et al. (2019); Fremstad and Paul (2019) or the second chapter of this dissertation (Ravigné et al., 2022).

[5] We can also cite Romero-Jordán et al. (2016), which finds electricity price elasticities in Spain to be U-shaped along income and income elasticities to be N-shaped causing vulnerability of low-income households to the economic crisis and price increase.

section 4, we present the price and income elasticities for 40 classes of households on 14 goods. In section 5, we analyse the microsimulation results. We study the impacts of various carbon price and recycling mechanisms, as well as a sensitivity analysis. Section 8 concludes.

2 A "toy-model" of backfire effects of carbon pricing

In this chapter, we aim to quantify the backfire effect in emissions of recycling carbon tax revenues towards households and derive the conditions under which it can happen. It is intuitively simple to understand how a backfire effect can take place. We try to formalise and illustrate it via a theoretical model of consumer demand. We first present a simplified model with limited heterogeneity in households. We then add step-wise heterogeneity with multiple carbon-emitting goods, several households and heterogeneity in the carbon intensities of goods and heterogeneous preferences.

Two mechanisms are put forward that operate through taxation and redistribution: the monetary transfer between households and the transfer between goods within a household basket.

We highlight four different levers influencing a possible backfire effect through the previous two mechanisms:

1. Respectively low and high price and income elasticities for carbon-intensive good;
2. Heterogeneous carbon intensities;
3. Energy-intensive households;
4. Revenues recycling favouring the energy-intensive households.

We can add a fifth one, which is heterogeneous price and income elasticities between households. We model an economy where price and income elasticities are predetermined for households. We do not explicitly consider the utility of households, and do not address utility maximisation for agents or of a benevolent planner. The objective is to assess, given preferences, how the emissions of households subject to a tax and revenue recycling evolve. The productive sector is not modelled either, but it implicitly rests on production functions using only labour, allowing an adjustment of supply and demand.

After each extension of the model, we offer conclusions on the conditions allowing a backfire effect to take place.

2.1 Re-allocating households income

An increase in the price of a specific good — say due to a carbon tax — triggers a reduction in the consumption of this specific good.[6] While when a household receives

[6] And triggers a substitution with other goods (note that we have no cross-elasticity in this chapter).

extra income, it will be distributed across all consumption goods, unless it is earmarked. Hence, a tax and revenue recycling have asymmetric effects on the consumption structure of the household.

Let's consider a single household consuming two goods, a polluting energy good E, and a non-polluting good X. We consider the expenditure in constant euros of each good at time i: E_i and X_i. Respective prices are p_i^E and p_i^X.

A single polluting good The carbon intensity of the energy good per euro spent is $\eta_E > 0$, while $\eta_X = 0$ (this hypothesis will be released in the next sections).[7] Carbon emissions at time 0 are then $\chi_0 = E_0\eta_E$ and at time 1, $\chi_1 = E_1\eta_E$.

The energy good E is taxed with a tax t per ton of carbon. The implementation leads to a price increase: $p_1^E = p_0^E(1 + \eta_E t)$. The relative price change of the energy good is then:

$$\frac{p_1^E - p_0^E}{p_0^E} = \eta_E t. \tag{1.1}$$

The household adjusts its demand to price and income increases with price elasticities, ε_p^E et ε_p^X, and income elasticities ε_r^E et ε_r^X.

The demand for each of these goods between the two periods is governed by the following system, where S is the carbon tax collected:

$$\begin{cases} E_1 = E_0(1 + \varepsilon_p^E \eta_E t)\left(1 + \varepsilon_r^E \dfrac{S}{E_0 + X_0}\right) \\ X_1 = X_0\left(1 + \varepsilon_r^X \dfrac{S}{E_0 + X_0}\right) \\ S = E_1 \eta_E t \end{cases} \tag{1.2}$$

The solutions of this system are:

$$\begin{cases} X_1 = X_0 \dfrac{1 - (\varepsilon_r^E - \varepsilon_r^X)\dfrac{E_0}{B_0}\eta_E t(1 + \varepsilon_p^E \eta_E t)}{1 - \varepsilon_r^E \dfrac{E_0}{B_0}\eta_E t(1 + \varepsilon_p^E \eta_E t)} \\ E_1 = E_0 \dfrac{\dfrac{E_0}{B_0}(1 + \varepsilon_p^E \eta_E t)}{1 - \varepsilon_r^E \dfrac{E_0}{B_0}\eta_E t(1 + \varepsilon_p^E \eta_E t)} \end{cases} \tag{1.3}$$

with B_0, the initial budget, $B_0 = X_0 + E_0$.

We impose that the budget is balanced ($B_1 = B_0$) and that the government redistribute all the carbon tax revenues.

[7] It is important to notice that η_E and η_X are expressed as carbon intensities of the expenditures, it explains why we do not express the carbon tax as an excise tax.

There is a backfire effect if emissions increase, i.e. if emissions at time 1, χ_1, are higher than the pre-tax level χ_0 at time 0 — that is if $\frac{\chi_1}{\chi_0} - 1 > 0$. We can express this growth rate as follows:

$$\frac{\chi_1}{\chi_0} - 1 = \frac{\eta_E t \left(\varepsilon_p^E + \frac{E_0 \varepsilon_r^E}{B_0}(1 + \varepsilon_p^E \eta_E t) \right)}{1 - \frac{\varepsilon_r^E E_0^p \eta_E t}{B_0}(1 + \varepsilon_p^E \eta_E t)}. \tag{1.4}$$

The growth rate in emissions (1.4) is always negative (details in appendix 1.A.1). Intuitively, since 100% of the tax is levied on the polluting good while the revenue is spent on the two goods, consumption of energy and thus emissions are reduced. The conclusion is that taxing and giving everything back to the same household does indeed reduce emissions. There can be no backfire effect under these conditions.

We highlight the first lever to have a backfire effect: it needs at least two polluting goods to occur.

Two polluting goods We can find a backfire effect if the second good X is also carbon-emitting. We assume that $0 < \eta_X < \eta_E$. X is then taxed accordingly at the same rate t as the energy good.

The intuitive situation where we can have a backfire effect is the following: very price inelastic demand in energy but high income elasticity. These are typical of a household in energy poverty.

The growth rate in emissions is expressed as follows:[8]

$$\frac{\chi_1}{\chi_0} - 1 = \frac{\left(\varepsilon_p^E \eta_E^2 t E_0 + (1 + \varepsilon_p^E \eta_E t) \chi_0 \frac{\varepsilon_r^E E_0 \eta_E t}{B_0} \right) + \left(\varepsilon_p^X \eta_X^2 t X_0 + (1 + \varepsilon_p^X \eta_X t) \chi_0 \frac{\varepsilon_r^X X_0 \eta_X t}{B_0} \right)}{1 - \frac{\varepsilon_r^E E_0 \eta_E t}{B_0}(1 + \varepsilon_p^E \eta_E t) - \frac{\varepsilon_r^X X_0 \eta_X t}{B_0}(1 + \varepsilon_p^X \eta_X t).} \tag{1.5}$$

Two conditions must be met to obtain a backfire effect:

1. The consumption of E increases. In other words, the income effect on E is greater than the price effect on E. Since the budget is constant, if E consumption increases, then X consumption decreases.[9] There is a transfer from the clean good to the polluting good. The condition is as follows:

$$\chi_0 t \frac{\varepsilon_r^E}{B_0} E_0 > -\varepsilon_p^E \eta_E t E_0. \tag{1.7}$$

[8] Equations and solutions to the demand system are expressed in appendix 1.A.2.

[9] Symmetrically,

$$\chi_0 t \frac{\varepsilon_r^X}{B_0} X_0 < -\varepsilon_p^X \eta_X t X_0. \tag{1.6}$$

.

That is to say, the increase in E consumption when the sum $\chi_0 t$ is recycled is greater than the decrease in E consumption when subjected to a price increase $\eta_E t$.

2. The carbon intensities must be different so that a transfer of X to E results in an increase in emissions. In the case where both goods are equally emitting, then obviously, a transfer between goods does not change anything. The condition is:

$$E_0 \frac{\varepsilon_r^E}{B_0} \chi_0 \left(1 + X_0 \varepsilon_p^X t \eta_X \frac{(\eta_X - \eta_E)}{\chi_0}\right) + \varepsilon_r^X \frac{\chi_0}{B_0} X_0 \eta_X t (1 + \varepsilon_p^X \eta_X t) - \varepsilon_p^X \eta_X X_0 > 0. \tag{1.8}$$

We can understand it as:

$$E_0 \cdot (\text{E income effect}) \left(1 + (\text{X price effect}) \cdot \frac{X_0(\eta_X - \eta_E)}{\chi_0}\right) + X_0 \cdot (\text{X total effect}) > 0$$

If $\eta_X = \eta_E$ then we have a backfire if the income effect on E (increase in consumption of E after recycling) more than compensates for the decrease in consumption of X, i.e. the income elasticity of E is large and also compensates the price effect on E. If on the contrary, we have $\eta_E \gg \eta_X$ then we create a strong multiplier effect on the income effect of E (the price effect on X is totally offset by the income effect on E).

We can therefore translate the condition of a backfire effect as: the dirty good must be significantly dirtier than the clean good. Its income elasticity must be high while its price elasticity is low (or similarly that the price effect of the clean good is high and the income elasticity is low), which implies an increase in the consumption of dirty good E.

This result may seem surprising and violate a number of assumptions about the rationality of agents. It would be irrational to reallocate expenditures when faced with a simultaneous tax and lump-sum transfer. However, in practice, carbon taxation takes place at the same time as consumption, while recycling of carbon tax revenues will likely take place once or twice a year, or could even be redistributed in the form of tax credits (for those paying enough taxes, as a direct cash transfer for the others) as it is the case in British-Columbia, Canada.

We conclude that emissions can decrease — or increase — when the carbon tax collects with one hand and gives it back with the other. We highlight two levers of backfire: the asymmetry between the carbon-intensive low price elasticity and high income elasticity and the difference in carbon content between the two goods.

2.2 Transfers between households

Now let's suppose we have two households: a 'poor' household that consumes (E_0^P, X_0^P) and a rich household that consumes (E_0^R, X_0^R). Without loss of generality, we suppose that the poor household is relatively more energy-intensive than the rich one: $E_0^P/X_0^P > E_0^R/X_0^R$. A fraction x of the total carbon tax revenues collected is given back to the poor household, and the remaining $(1 - x)$ to the other household.

One polluting good If we assume that only the good E is carbon-emitting, then there is again no possibility of a backfire effect. Indeed, the within-households effect, from E to X, means a decrease in emissions. In the most extreme case, the total amount collected on E is redistributed to only one of the households ($x = 1$ or $x = 0$) that spends it all on the energy good. The total amount spent on E is the same as the pre-taxed level and the impact on emissions is neutral.

Two polluting goods We shall then consider $0 < \eta_X < \eta_E$.

The program of consumption at time 1 is:

$$\begin{cases} E_1^P = E_0^P(1+\varepsilon_p^E \eta_E t)\left(1+\varepsilon_r^E \dfrac{xS}{E_0^P + X_0^P}\right) \\ X_1^P = X_0(1+\varepsilon_p^X \eta_X t)\left(1+\varepsilon_r^X \dfrac{xS}{E_0^P + X_0^P}\right) \\ E_1^R = E_0^R(1+\varepsilon_p^E \eta_E t)\left(1+\varepsilon_r^E \dfrac{(1-x)S}{E_0^R + X_0^R}\right) \\ X_1^R = X_0^R(1+\varepsilon_p^X \eta_X t)\left(1+\varepsilon_r^X \dfrac{(1-x)S}{E_0^R + X_0^R}\right) \\ S = (E_1^P + E_1^R)\eta_E t + (X_1^P + X_1^R)\eta_X t \end{cases} \tag{1.9}$$

with $B_0^R = X_0^R + E_0^R$ et $B_0^P = X_0^P + E_0^P$, $\chi_0^E = (E_0^R + E_0^P)$, $\chi_0^X = (X_0^R + X_0^P)$, $B_0^R = (E_0^R + X_0^R)$, $B_0^P = (E_0^P + X_0^P)$.

The expression of $\chi_1/\chi_0 - 1$ is not very telling (see (1.33) in appendix 1.A.3). Let us instead consider the sensitivity of this expression to x, the recycling key of the carbon tax revenues (see equation (1.34) in appendix):

$$\frac{\partial\left(\dfrac{\chi_1}{\chi_0} - 1\right)}{\partial x}.$$

The sign of this expression is independent of x. It is positive when the following condition (1.10) is met:

$$\varepsilon_r^X \eta_X (1+\varepsilon_p^X \eta_X t) < \varepsilon_r^E \eta_E (1+\varepsilon_p^E \eta_E t). \tag{1.10}$$

We can understand this equation as follows: emissions of E are more sensitive to new income that X. It takes into account the fact that the remaining share of consumption after carbon tax $(1+\varepsilon_p^E \eta_E t^)$ and $(1+\varepsilon_p^X \eta_X t)$ might be different between the goods. A huge income elasticity or carbon intensity might no compensate the fact that there is little consumption to grow back. We will hereafter refer to these weighted income elasticities as "carbon income elasticities".

Then one euro recycled towards the energy-intensive household will increase emissions relatively more than if that euro is recycled towards the other household.

More precisely, when the income effect for the energy good weighted by the carbon intensity η_E is greater than the income effect in the other good X also weighted by its carbon intensity η_X (1.10), then the growth rate of emissions reduction grows (positively) with x. That is, if the more the recycling of the carbon tax revenues is focused on the energy-intensive household, the less emissions decrease.

Skewed recycling mechanism The greatest risk of backfire is reached when the full carbon tax revenues is recycled towards the energy-intensive household P. Let us have a look at this situation where $x = 1$ and the condition (1.10) is met.

The sign of growth rate of emissions (see (1.36) in appendix) depends on (1.11):

$$\varepsilon_p^E \eta_E t \chi_0^E + \varepsilon_p^X \eta_X t \chi_0^X + \chi_0 \left(\varepsilon_r^X \frac{X_0^P}{B_0^P} \eta_X t (1 + \varepsilon_p^X \eta_X t) + \frac{E_0^P}{B_0^P} \varepsilon_r^E \eta_E t (1 + \varepsilon_p^E \eta_E t) \right). \quad (1.11)$$

The two terms of the price effect ($\varepsilon_p^E < 0,\ \varepsilon_p^X < 0$) are negative, and the terms of the income effect are positive. The sign of the expression then depends on which effect prevails over the other, and there can be several combinations.

If we assume that $\varepsilon_r^X \eta_X (1 + \varepsilon_p^X \eta_X t) < \varepsilon_r^E \eta_E (1 + \varepsilon_p^E \eta_E t)$, it implies that emissions grow with x (note that we have maximised x: $x = 1$). Then the relationships between the quantities consumed E_0^P and X_0^P and the price elasticities weighted by the elasticities and emissions at time 0, $\varepsilon_p^E \eta_E \chi_0^E$, and $\varepsilon_p^X \eta_X \chi_0^X$ govern the sign of the expression.

There are many possible combinations. Let us take one for example: if the energy is not very price elastic (less than X), it follows that:

$$\varepsilon_p^E \eta_E > \varepsilon_p^X \eta_X.$$

It means that energy goods (which are essential) are less elastic in emissions than other goods. Then, a backfire effect takes place if:

$$\varepsilon_r^X \eta_X (1 + \varepsilon_p^X \eta_X t) \frac{X_0^P}{B_0^P} > -\chi_0^E \varepsilon_p^E \eta_E - \chi_0^X \varepsilon_p^X \eta_X,$$

which implies that the carbon income elasticities of X are greater than the carbon price elasticities of E and X.

We see two intertwined effects (whereas in the section 2.1, we only had one) that is the relationship between price and income elasticities, weighted by consumption — the energy intensity (E_0^P / X_0^P) of the budget of poor households — and aggregate consumption — in fact, aggregate carbon emissions per good (χ_0^E / χ_0^X).

We highlight a third backfire lever: very energy-intensive household consumption will facilitate the occurrence of a backfire effect. It is because the revenues collected are larger, meaning that the effects are potentially larger too. This lever obviously combines with the second, a large difference in carbon content between the two goods.

Conversely, even if the growth rate of emissions is decreasing with x, and we take $x = 0$ (i.e. we give the full revenue back to the least energy-intensive household), then we can still have a backfire effect (see (1.37) in appendix 1.A.3).

General recycling mechanism If we move from $x = 1$ to $\forall x$, then we highlight a fourth lever of the backfire: a recycling mechanism biased towards the most carbon-intensive household.

In the following expression of the growth rate of emissions (1.12), we can clearly see the four levers that are intertwined: the relations between elasticities, the energy intensity of both households (which drives the total emissions at time 0), and also the value of x. This last lever works through the terms in $x\chi_0$ and $(1-x)\chi_0$.

In all generality, we have:

$$\begin{aligned}
\frac{\chi_1}{\chi_0} - 1 = t\Big[&\chi_0^E \varepsilon_p^E \eta_E^2 + \eta_X^2 \chi_0^X \varepsilon_p^X \\
&+ \chi_0 \varepsilon_r^E \eta_E (1 + \varepsilon_p^E \eta_E t) \left((1-x) \frac{E_0^R}{B_0^R} + x \frac{E_0^P}{B_0^P} \right) \\
&+ \chi_0 \varepsilon_r^X \eta_X (1 + \varepsilon_p^X \eta_X t) \left((1-x) \frac{X_0^R}{B_0^R} + x \frac{X_0^R}{B_0^R} \right) \Big] / \\
&\Big[1 - \left(\frac{E_0^R}{B_0^R}(1-x) + x \frac{E_0^P}{B_0^P} \right) \varepsilon_r^E \eta_E t (1 + \varepsilon_p^E \eta_E t) \\
&- \left(x \frac{X_0^P}{B_0^P} + (1-x) \frac{X_0^R}{B_0^R} \right) \varepsilon_r^X \eta_X t (1 + \varepsilon_p^X \eta_X t) \chi_0 \Big].
\end{aligned} \tag{1.12}$$

The denominator of this expression is always positive to ensure the balance of the overall budget. The higher the income elasticities are, the closer to zero the denominator will be, and therefore the greater the multiplier effect on the backfire effect.

We can clearly see the four levers in the numerator: the interplay between income elasticities (i) is weighted by the energy (ii) and other goods intensities of each household (iii) and the share of revenues accruing to each of them (iv). This function can be rewritten to highlight the role played by energy intensity and the role of redistribution (1.13). Even if the income elasticity of E outweighs that of X, then it will still be weighted by the consumption structure of each household, and by the recycling mechanism with x.

$$\begin{aligned}
t\Big[&\chi_0^E \varepsilon_p^E \eta_E^2 + \eta_X^2 \chi_0^X \varepsilon_p^X \\
&+ \chi_0 (1-x) \left(\varepsilon_r^E \eta_E (1 + \varepsilon_p^E \eta_E t) \frac{E_0^R}{B_0^R} + \varepsilon_r^X \eta_X (1 + \varepsilon_p^X \eta_X t) \frac{X_0^R}{B_0^R} \right) \\
&+ \chi_0 x \left(\varepsilon_r^E \eta_E (1 + \varepsilon_p^E \eta_E t) \frac{E_0^P}{B_0^P} + \varepsilon_r^X \eta_X (1 + \varepsilon_p^X \eta_X t) \frac{X_0^P}{B_0^P} \right) \Big].
\end{aligned} \tag{1.13}$$

2.3 Heterogeneous preferences

Intuitively, and without complex calculations: if households have different elasticities, then we can add two levers favouring a backfire effect: (v) the most energy-intensive households are also the least price elastic and (vi) they are the most income elastic on energy goods.

The term
$$\chi_0 \varepsilon_r^E \eta_E (1 + \varepsilon_p^E \eta_E t) \left((1-x) \frac{E_0^R}{B_0^R} + x \frac{E_0^P}{B_0^P} \right)$$
becomes
$$\chi_0 \left((1-x) \varepsilon_r^{ER} \eta_E (1 + \varepsilon_r^{ER} \eta_E t) \frac{E_0^R}{B_0^R} + x \varepsilon_r^{EP} \eta_E (1 + \varepsilon_p^{EP} \eta_E t) \frac{E_0^P}{B_0^P} \right).$$

This gives even more possibilities for the levers to compensate each other to create a backfire: a high income elasticity or low price elasticity of the energy-intensive household (P) will be able to compensate for a more moderate energy intensity of consumption, or a low difference in carbon-intensities between goods.

Conversely, one can also imagine limiting the backfire effect by playing on the share of carbon tax revenues recycled towards households. If only a portion of the γ was redistributed to households, the terms of the income effect would be linearly weighted by $\gamma < 1$, which would reduce the chances of having a backfire effect.

If we suppose that part of the tax is paid by firms — and not only by households — with a pass-through lower than one, then the price of goods no longer increases by $\eta_E t$ but by $\sigma \eta_E t$ with $0 < \sigma < 1$. It is actually similar to having different carbon intensities but adds a new degree of freedom. Thus, the total amount paid by households and passed on would be lower but the different effects would be the same. However, if the pass-through coefficient were different for the two goods, then we would see yet another lever. If the pass-through coefficient of good X was lower than that of good E, then it would limit the transfer between the two goods, and the amount collected on X would be lower. But this would also increase the carbon intensity differential of consumption of goods X and E for the consumer. This lever would have ambiguous effects on emissions.

The more heterogeneity we add, i.e. more goods, more households with heterogeneous preferences and consumptions, the more we increase the number of combinations of parameters leading to a backfire effect.

From this compact "toy model", we can derive several conditions under which we risk having a backfire effect: the recycling of carbon tax revenues is targeted towards particularly carbon-intensive households. These households are relatively inelastic to the carbon tax on these polluting goods but very elastic on other less carbon-intensive goods, and most of the rebated income is devoted to carbon-intensive expenditure (the income elasticities of carbon-intensive goods are relatively higher than those of other goods).

3 Methods and Data

In this section, we apply the equations of section 2 to a consumer expenditures survey database to perform the microsimulation assessment of the potential backfire effect of a carbon tax and its recycling by lump-sum transfer to households. We first introduce the data (section 3) and the microsimulation framework (section 3.2).

We find in section 2 that the interplay of income and price elasticities drive the aggregate reduction in emissions. We will therefore need to estimate the price and income elasticities of households. We detail the methodology in section 3.3 and analyse the elasticities in section 4.

3.1 Data

Budget de Famille We use the French Consumer Expenditures Survey ("Budget de Famille") This survey has been carried out every 5 to 6 years since 1979 by the French public statistical institute INSEE. It contains self-reported data on households: socio-economic characteristics, sources of income and expenditures.

To estimate elasticities, we harmonise the Consumer Expenditures Survey from 1979 to 2010. We use the 2010 version to microsimulate the impacts of the carbon tax and recycling to households.

We build the database from the harmonisation of seven consecutive French Household Expenditures Surveys from 1978 to 2011 (1978-1979, 1984-1985, 1989, 1994-1995, 2000-2001, 2006, 2010-2011). Each survey consists of about 10000 households[10] that report their consumption for 7 days. Expenditures are classified in items compatible with the European nomenclature COICOP (Classification Of Individual Consumption Of Purpose). Households also report income since the 1994-95 survey. They indicate all types of resources: taxable income, social benefits, inter-household transfers, etc. According to socio-economics characteristics, each household is given a weight to ensure the representativeness of the sample by aggregation. We group expenditure items into 14 aggregates,[11] four of which energy products. It answers the objective of the study to describe households' behaviour when facing a carbon tax, particularly on energy consumption. We decide to include construction expenditures as a specific consumption item rather than as an investment of the households following (Berry et al., 2016). This nomenclature is consistent over the seven successive surveys.

Prices We follow Clerc and Marcus (2009) and Ruiz and Trannoy (2008) to build individual price index for each household for the 14 goods. For each household, the 14 price indices are calculated by using a geometric mean of the price indices of the items of the INSEE database, weighted by the specific weights of each of these items in the 14 aggregated items.

[10] Number of households per Consumer survey: 9403 (1979); 11 652 (1985); 8829 (1989); 9633 (1995); 10 305 (2001); 10 240 (2006); 10 342 (2010).

[11] Food, Electricity, Gas (natural and biogas), Other residential energy, Construction and construction services, First-hand vehicles, Vehicle fuels and lubricants, Rail and air transport, Road and water transport, Leisure services, Other services, Other consumption/equipment goods, Housing rents, Second-hand vehicles.

Vulnerability types We assume that income influences demand through specific elasticities – both income and price – for income deciles, but also that non-income related characteristics such as the location (urban/rural), age, household composition, job, etc., can influence elasticities. Therefore, we divide each cross-section of data between 10 deciles of income (Sun and Ouyang 2016) and 4 types of households describing "economic vulnerability". We classify households from the 2010-2011 consumer survey in 4 vulnerability types using principal component analysis on two types of variables: income structure – in shares of wages, social benefits, capital income and others income – and shares of pre-committed expenditures in their budget (Quinet and Ferrari, 2008; Nadaud, 2021). A detailed analysis of the socio-economic characteristics of the vulnerability classes allows us to establish the following dominant profiles in each class (which does not mean that no other household belongs to the same type):

- Type I: Young working-class households who are tenants in large cities or Paris (medium income deciles);
- Type II: Isolated elderly households with low-income tenants in large cities;
- Type III: Working households with higher standards of living owning their homes in small towns;
- Type IV: Elderly households owning their homes in rural areas (low to medium income deciles).

We estimate for each year of the survey, the vulnerability type of each household (see (Nadaud, 2021) for all details).

Cells For the estimation of elasticities, the database is then composed of 40 household classes — a cell is an income decile crossed with a vulnerability type — at 7 years, which gives 280 cells. For each of these cells we aggregate income, expenses and prices.

Carbon intensity We use the database of Pottier et al. (2020), which estimates the carbon intensity of consumption from the French Household Expenditures Surveys 2010-2011. For each item in our nomenclature, we aggregate the carbon intensities of the goods that compose it with the aggregate structure of household consumption. We obtain carbon intensities (emissions per euro spent) for each of the 14 goods in our nomenclature common to all households (Appendix 1.C.2).[12]

[12]The carbon footprint of electricity may seem surprisingly high considering the French energy mix which relies heavily on nuclear plants with low GHG emissions. This may be due to two reasons: some electricity and gas bills are inseparable, the split of Pottier et al. while legit may bias the real consumption; or the investments in electricity production bias the result. We study the impact of high carbon-intensity of electricity in appendix 1.C.2.

3.2 Microsimulation model

We focus on the distributional impacts of the carbon tax. We assume that the tax is fully passed through to consumers. The full-forward shifting of the tax is a standard assumption in the literature (Devulder and Lisack, 2020; Cronin et al., 2019; Metcalf et al., 2010; Owen and Barrett, 2020), because the relation between a specific market and the pass-through coefficient is ambiguous (Fullerton and Muehlegger, 2019). Newly empirical evidence points to a pass-through on only 70% of a carbon tax to consumers, reducing the welfare cost for households (Ganapati et al., 2020); nevertheless, they only provide estimates for a couple of industries.

The microsimulation is a 2-step process: the price effect of the carbon tax and the income effect of recycling the carbon tax revenues to households. The introduction of the carbon tax causes a rise in the price of each item j, for each household. Its consumption E_j^1 at time 1 is then to decrease to a level:

$$E_j^1 = E_j^0 \times \left(1 + \varepsilon_p^j \frac{\Delta p_j}{p_j}\right)\left(1 + \frac{\Delta p_j}{p_j}\right), \tag{1.14}$$

with the increase in price $\Delta p_j / p_j$ being equal to the carbon intensity of the expenditures multiplied by the level of the tax.

The lump-sum transfer S increase consumption at time 2 following:

$$E_j^2 = E_j^1 \times \left(1 + \varepsilon_r^j \frac{S}{\sum_j E_j^0}\right). \tag{1.15}$$

We assume constant saving rates for each household throughout the simulation. Since we have not computed price elasticities in a system and do not have cross-elasticities, we ensure the closure of the system by allocating surplus and shortfall of consumption on all other budget items using the estimated income elasticities. Our demand system is not far from being balanced and the closure procedure has little bearing on our results (see appendix 1.B.3). It might introduce a small bias to close budget between the price and the income steps, but it is necessary since we then compare the magnitude of the two effects.

The ratio of net surplus S over total consumption is treated as extra-income (whether it is positive or negative). As previously, we iterate the process to ensure the closure of the system (the closure condition is that the aggregate consumption between the original database and the carbon tax budget of households should differ no more than 10^{-7}). To ensure convergence, we remove at each iteration the households with a ratio of net surplus over total consumption higher than 15%. The representativeness of the database is not affected, as these households represent less than 0.3% of the data.

We iterate to ensure the budget is balanced at the end of the 'price effect' step and the 'income effect' step. We finally iterate the whole process — including price and income effects — to ensure the full carbon tax collected it recycled to households. The lump-sum transfer increases household consumption, including that of taxed goods thus increasing the volume of carbon tax revenues. We ensure convergence at the 0.01% threshold (10^{-4}) between the collected and recycled carbon tax. The first two iterations are nested within this one.

3.3 Estimating elasticities

We estimate price and income elasticities for the 14 items defined in our nomenclature using the Linear-Approximate Almost Ideal Demand System – LAIDS (Green and Alston, 1990; Buse, 1994). LAIDS is an approximation of the Almost Ideal Demand System (AIDS) model developed by Deaton and Muellbauer (1980). It is a flexible expression of the Engel curve using the linear Stone price index (1.16) which allows for harmonious aggregation over consumers (Irfan et al., 2018; Labandeira et al., 2017). LAIDS is widely used for empirical studies, see for instance Armagan and Akbay (2008); Piggott and Marsh (2004) and especially for energy demand (Sommer and Kratena, 2017; Sun and Ouyang, 2016; Ngui et al., 2011; Gundimeda and Köhlin, 2008). We follow Pawlowski and Breuer (2012) to add dimensions beyond price and income in the estimation. Non-income dimensions can represent supply-based opportunities, that is, the more or less difficult access to alternatives and substitution. For example, the price elasticity of gasoline depends on the availability of public transport services, it depends on location and not income.

For each of the 280 cells, we carry out a principal component analysis (PCA) of a certain number of quantitative variables: the type of household, the sex, the age of the reference person in seven groups, the occupation of the reference person, the occupation status of the dwelling, the population stratum of the household's residence, the region (ZEAT, Zone d'Études et d'Aménagement du Territoire), the year of construction of the main residence, the number of vehicles, whether the household is poor and lives below the thresholds of 50% and 60% of the median living standard (income based on the OECD equivalence scale). We perform a PCA for each cell for all variables. We retain the first five principal components as $(\gamma_k)_k$.

The Stone Price index P^* is expressed as

$$\log(P^*) = \sum_{i=1}^{14} w_i \log(P_i), \tag{1.16}$$

with w_i the budget share of the item i and P_i the price index of item i.

For each of the 280 cells[13] of our database which are the 40 classes of households over 7 surveys, we estimate the following Engel curve (1.17) which relates budget share w_i to the logarithms aggregated real expenditure of item i of the cell — nominal expenditures E_i deflated by the Stone Price index P^* — the item price P_i. e_i is the regression residual for item i equation. We add five socio-economic characteristics of the cell $(\gamma_k)_k$.

Importantly, we do only include the price of item i in the Engel curve when it is customary to include all the prices to estimate cross-impact. The reason is that the prices of the 14 goods are too correlated. Yet, the imputation of household-specific price indices introduces variability in prices. Moreover, the use of cross-sectional cells over a 30-year period reveals substitution between goods.

[13]We cannot call it a pseudo-panel since we do not follow cohorts in time. In pseudo-panels, these cohorts are agents identified by a number of variables stable over time (age, gender, degree) which form cells. The assumption is that one can track the cell in consecutive surveys.

$$w_i = a_i + b_i t + c_i \log\left(\frac{E_i}{P^*}\right) + d_i \log(P_i) + \sum_{k=1}^{5} \gamma_k + e_i. \quad (1.17)$$

We define the price and income elasticities, respectively e_{E_iX} and $e_{E_iP_i}$ for each good i with respect to each cell expenditure E_i, the average household income X and the price of this good P_i.

$$\begin{aligned} e_{E_iP_i} &= \frac{\partial E_i}{\partial P_i}\frac{P_i}{E_i} \\ e_{E_iX} &= \frac{\partial E_i}{\partial X}\frac{X}{E_i} \end{aligned} \quad (1.18)$$

For each item i, we derive the income and price elasticities as functions of the estimated parameters a_i, b_i, c_i and d_i. In this specification, the coefficients are interpreted as semi-elasticities of the budget share to real expenditure (X/P) and to price. Uncompensated elasticities for income and price are respectively (see appendix 1.B.1):

$$\begin{aligned} e_{E_iP_i} &= \frac{d_i}{w_i} - c_i \\ e_{E_iX} &= 1 + \frac{c_i}{w_i} \end{aligned} \quad (1.19)$$

Budget shares appear on both sides of the equation (1.17) within E_i/P^*. We solve this simultaneity issue using instrumental variables and two-stages least square method (Colonescu, 2016). In the first step, we use the real standard of living (income deflated by the number of consumption units of the cell, as per the OECD equivalence scale) as an instrument of the total nominal expenditure of the cell to approach budget shares $\hat{w}_i$. In the second step, we regress the Engel curve equation on $\hat{w}_i$ instead of w_i. As expected, the two variables are closely correlated and the instrumentation is strong for all cells.

We check for collinearity in the estimation model using the variance inflation factors (James et al., 2013) and the Besley, Kuh and Welsh (BKW) condition index test (Belsley, 1980; Silvey, 1969). In case of high collinearity, we drop the socio-economic variable $(\gamma_k)_k$ which adds more collinearity (step-wise selection).

It is not possible to estimate the equation for every 40 cells for the elasticities of domestic fuels - other than natural gas - and rents. The variability between prices and expenses across time is not high enough: we estimate these elasticities on the 10 income deciles.[14]

[14] The aggregation on deciles only leads us to divide the size of our sample by 4, from 280 observations (deciles x classes x years) to 70 (deciles x years). The precision of our estimate, which evolves by construction as the square of the sample size, was thus divided by two.

4 Elasticities Estimates

Most of our elasticities are significant at the 1% threshold (Table 1.B.1 in appendix 1.B.2).[15] Income elasticities are generally more significant than price elasticities. Indeed, in budget surveys, expenditures are well observed but not the real prices faced by households; that is why we build price series for each household (see section 3). Only three expenditure items are weakly significant at 10%: the price elasticity of second-hand vehicles, the income elasticity of domestic fuels other than gas and that of rents. The price elasticities of domestic fuels other than gas and both the income and price elasticities of transport services are significant at the 20% threshold. We perform an uncertainty analysis in the next section (see section 1.C.1) to assess the validity of the whole set of 1120 elasticities.

Despite not being estimated in systems because we do not estimate cross-elasticities, our estimates of elasticities form a quasi-consistent system (see 1.B.3).

Low long-term price elasticities characterise essential expenditure items. All household classes have a price elasticity between -0.5 and 0 for food, natural gas, gasoline, leisure goods, services, and other goods. Conversely, electricity, transport services (air & rail or water & road) and especially new vehicle purchases are characterised by more variability in price elasticity across households (Figure 1.1).

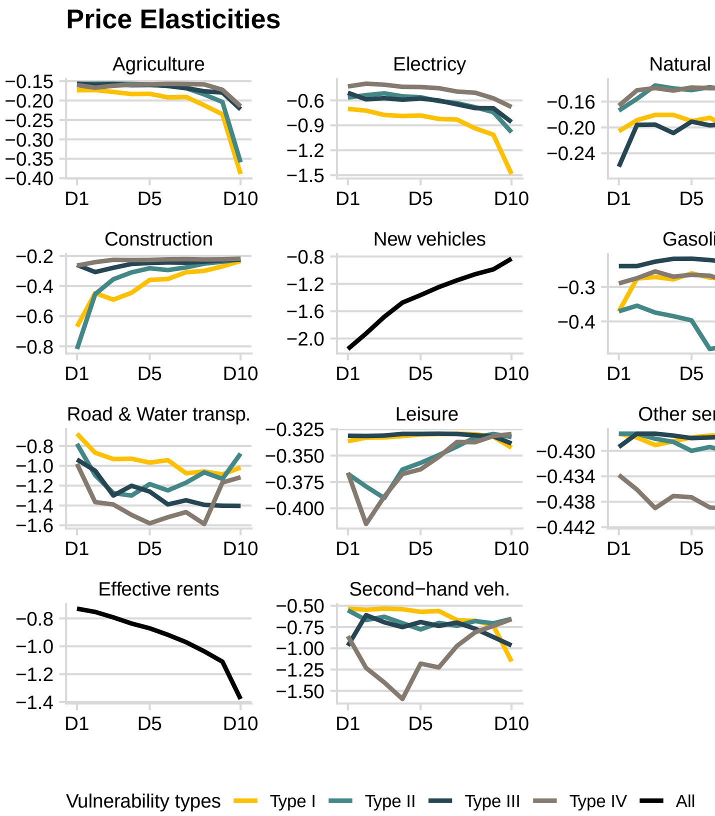
For instance, middle-income groups are more dependent on natural gas and gasoline than low and high-income groups: price elasticities are U-shaped across income deciles. Blundell et al. (2012) also finds that price elasticities for gasoline are lower for low- and high-income deciles than for middle-income households. We find that low-income households are dependent on agricultural goods, electricity, other energy, services and rents as price elasticities increase in absolute value towards the richer deciles. That is, poorer households have lower price elasticities for electricity and domestic fuels than richer households. Other expenditure items - construction, new vehicles, leisure or other consumer goods – allows the poorer household to close their budget as they show higher price elasticities than richer households.

Our estimates concur with those of Gardes (2014) and Gardes and Starzec (2018) on the same database using other methods. The meta-analysis of Labandeira et al. (2017) finds central values to be -0.600 for energy, -0.677 for electricity, -0.614 for natural gas, and -0.720 for gasoline. We have much lower estimates (in absolute values) for gasoline and natural gas, but more negative estimates for electricity. It might be because we estimate long-term elasticities, Deryugina et al. (2020) finds that the price elasticity for electricity is larger in the long run than in the short term.

Price elasticities are in general, not linearly related to income (Figure 1.1). Their profiles along income illustrate the essential goods for each group. On the contrary,

[15] Elasticities are computed as a non-linear function of coefficients of the Engel curve and approximated budget share ($\hat{w}_i$). Therefore the standard errors of income and price elasticities are not easily computed. We approximate the variance of the elasticities using the delta method —- that is a Taylor series approximation of the variance of functions of random variables (Casella and Berger, 2002; Colonescu, 2016) — see appendix 1.B.2.

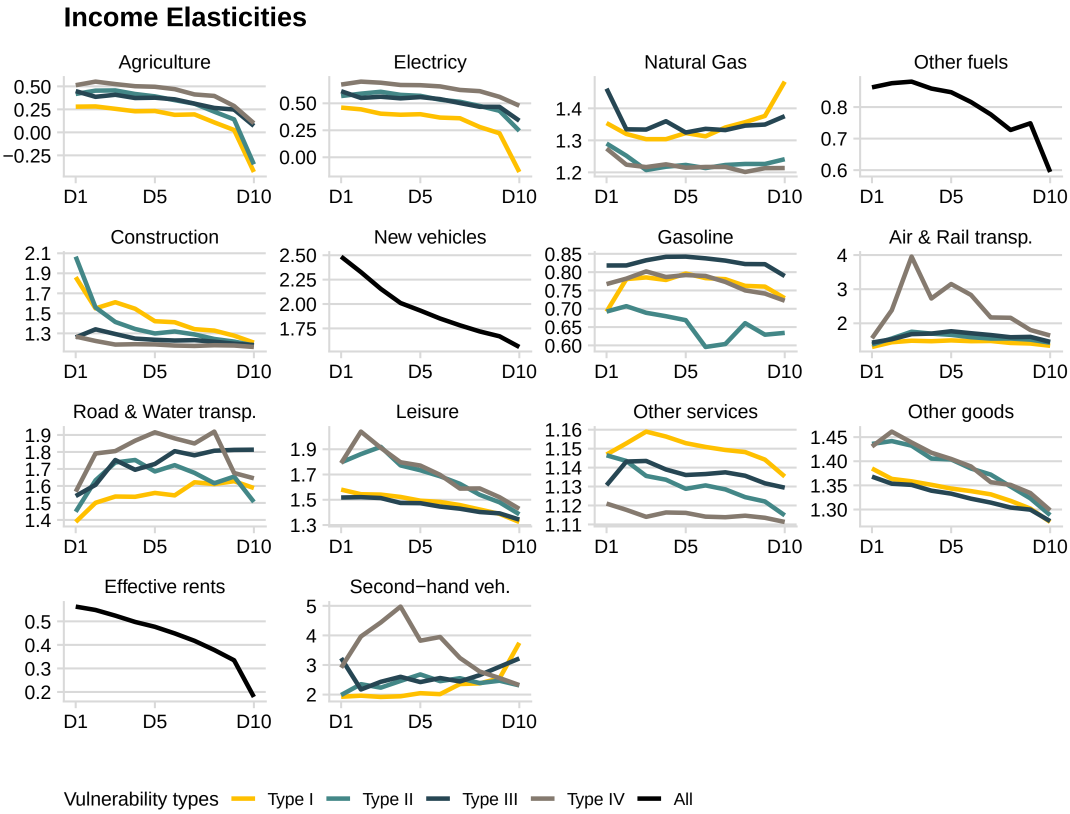
Figure 1.1 – Long-term price elasticities of French households by decile and vulnerability type



profiles of income elasticities across income are more similar to each other (Figure 1.2): D1 and D10 have similar values, while there is a decreasing trend from D2 to D9. These results echo the long-term elasticities in Clerc and Marcus (2009).

We find that urban dwellers — mostly represented in vulnerability types I and II — have a more elastic demand for gasoline than rural households. For instance, type I households — mostly young tenants living in large cities — in all income deciles have lower income elasticities than all other classes but also display a more negative price elasticity. Differences between urban and rural households — represented respectively by types I-II and III-IV — are particularly significant for extreme income deciles. Low-income urban dwellers show a higher price elasticity for building than the other two types; similarly, the richest urban dwellers have highly elastic demands for food and electricity. In terms of transport, older urban dwellers type II show, unsurprisingly, less dependence on fuel, with a price elasticity for this good higher than the other types. Rural and elderly (type IV) middle-class households show a high elasticity of demand for transport, second-hand vehicles and services. The poorest (D1-D2) and richest (D9-D10) rural and elderly households (type IV) have average behaviour regarding these items.

Figure 1.2 – Long-term income elasticities of French households by decile and vulnerability type



The divide is not only territorial between urban and rural areas but also generational: older households — mostly represented in types II and IV — show a lesser need for leisure and communication goods, especially among the less well-off (up to D8), this is also the case for "other consumption goods". Conversely, younger households — types I and III — have more elastic demands for energy but not for services. Studies based on French consumer surveys show that price elasticities vary greatly depending on income (Douenne, 2020) but also on other socio-economic variables (age group, urban or rural location, etc.) (Calvet and Marical, 2011).

We are the first to estimate price and income elasticities on as many goods and households. Our method has advantages and drawbacks. The main advantage is that we differentiate between carbon-intensive and low-carbon goods, and especially between energy goods. It allows for the proposed microsimulation and the estimation of the backfire effect. Two main drawbacks are that we are unable to estimate cross elasticities, and we cannot control for the endogeneity of prices and quantities in time. To estimate reliable elasticities, one needs an exogenous shock, as in Deryugina et al. (2020) that exploits a change in the choice of electricity provider and the negotiation of new contracts (and new prices) town by town in the US. We also do not differentiate between price and tax elasticity. It might have importance, as Andersson (2019) finds carbon tax elasticity of gasoline is three times larger than the price elasticity of gasoline in Sweden.

5 Microsimulation and application to the French carbon tax

5.1 Price signal: distribution of the decrease in emissions

A 158€/tCO_2 carbon tax[16] — covering both direct and indirect emissions — decreases aggregate households' emissions by 10.9%. It plays on three levers: the decrease in consumption of carbon-intensive goods (the so-called sufficiency), the substitution of other goods to carbon-intensive goods,[17] and energy efficiency since the long-term elasticities encapsulate the past trends in energy efficiency when energy prices have risen.[18] Since we do not have a general equilibrium model, we neglect the use of revenues collected by the government outside of direct revenue recycling to households in the form of lump-sum transfers. In this section 5.1 we assume that the use of the revenues levied are not carbon-emitting.

Prior to any compensation mechanism, carbon pricing is regressive when applied on both direct and indirect emissions of households: it weights disproportionally on poorest households as they dedicate a more important share or income to carbon-intensive items (Figure 1.3). The first income decile D1 — the bottom 10% of the income distribution according to the OECD equivalence scale[19] — dedicates 9.2% of their income to carbon tax, and 5.7% of their total expenditures whereas the top income income decile D10 dedicates 3.0% of their income and 4.7% of their expenditures to carbon tax.

We show that regressivity is clear when carbon tax is compared against income: the share of income dedicated to carbon tax decreases with each income decile. When compared against total expenditures, the carbon tax is only regressive from D5 to D10 since the first half of the income distribution dedicates between 5.7 and 5.9% of their total expenditures to carbon tax. As Pottier (2022) explains, we know that the saving

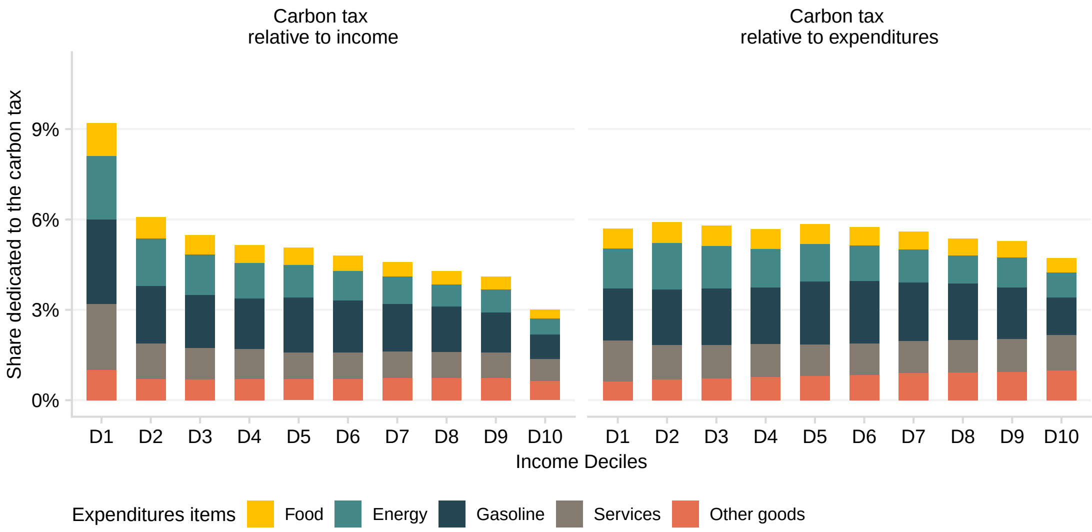
[16] Level of carbon tax in 2025, since abandoned.

[17] Although we do not have cross-elasticities in our model, the historical trends provided by the use of several consumer expenditures survey encapsulate some of the substitutions.

[18] Long-term elasticities capture a number of effects, including fuel-efficiency trends or behavioural change. A small increase in gasoline prices over time may be characterised by a high gasoline elasticity, which reflects the continued improvement in vehicle consumption. But households have also increased their mobility needs over the same period which may counteract the previous overestimation of elasticity. Calvet and Marical (2011) estimates gasoline elasticities, taking into account the improvement in vehicle consumption over 20 years. They use the price of the fuel required to drive 100km and not the price per litre.

[19] It OECD scale represents the number of consumption units of the households: one share for the first adult, half a share for each subsequent adult, 0.3 per child.

Figure 1.3 – Relative weight of carbon pricing for households



Note: In the left-hand panel the aggregate volume of carbon tax paid by each income decile is compared to the aggregate disposable income, in the right-hand panel the volume of carbon tax is compared to the volume of total consumption. The difference is savings or debt.

rate increases with income. Hence, an increase in income triggers a lesser increase in expenditure and thus in carbon footprint. We can conclude that the carbon tax burdens more the low-income households relative to both their income and total expenditures.

Feindt et al. (2021) finds that the carbon tax may be slightly progressive in a number of countries when considering the full carbon footprint of households. In the US Metcalf (2019); Cronin et al. (2019); Hassett et al. (2009) find the carbon tax to be progressive. Fremstad and Paul (2019) find that the carbon tax without recycling is regressive when compared against both income and expenditures.

The heterogeneity in preferences increases the regressivity of the carbon tax since low-income households have lower price elasticities for the most polluting goods (except natural gas, but the gradient across deciles is small) compared to higher income households.

The main share of carbon tax comes from fuel and energy bills for all income deciles. But the weight of these two items and of food decreases with income. This drives the regressivity of carbon pricing. We demonstrate the assumption in section 2 that low-income households are also the most energy-intensive. It will therefore be necessary to compensate the poorest households (which we translated with x close to 1 in the theoretical model, section 2), which increases the risk of backfire. These are the largest emissions items, but they are also the ones on which households are making the greatest effort, reducing their fuel-related emissions by 14% to 17% (compared to an average of 10.9%).

The effort to reduce emissions is not homogeneous between households. Figure 1.4 plots the decrease in emissions for an item due to the carbon pricing against the share of households with non-zero expenses for that item. Zero fuel expenditure may indicate that a household does not own a car (this is the case for 19% of households on average, but 41.1% of D1, and only 8.8% of D9 and 10.6% of D10) or that they did not fill their tanks during the survey expenditure collection period.[20] D1 households have paradoxically the lowest number of gasoline consumers and are the most impacted in terms of budget share[21] and consumption reduction. Middle-income classes (D2-D8) are more fuel dependent than extreme deciles, hence a smaller reduction in real consumption of gasoline. Unsurprisingly, they were dominant in the Yellow Vests events in France in 2018 (Delpirou, 2018). Conversely, D1 electricity demand is relatively inelastic in price compared to high-income deciles - price elasticity is -1.032 for D10 against -0.56 for D1 and D2. Consumption of natural gas is more homogeneous. Unsurprisingly, as with gasoline, low-income households (D1-D3) already consume less leisure than other households (only 85-90% report leisure expenditure compared to 100% for households D7-D10) and would make a reduction of nearly 6% in this item of expenditure due to the carbon tax (although leisure goods are by far the least carbon intensive of all).

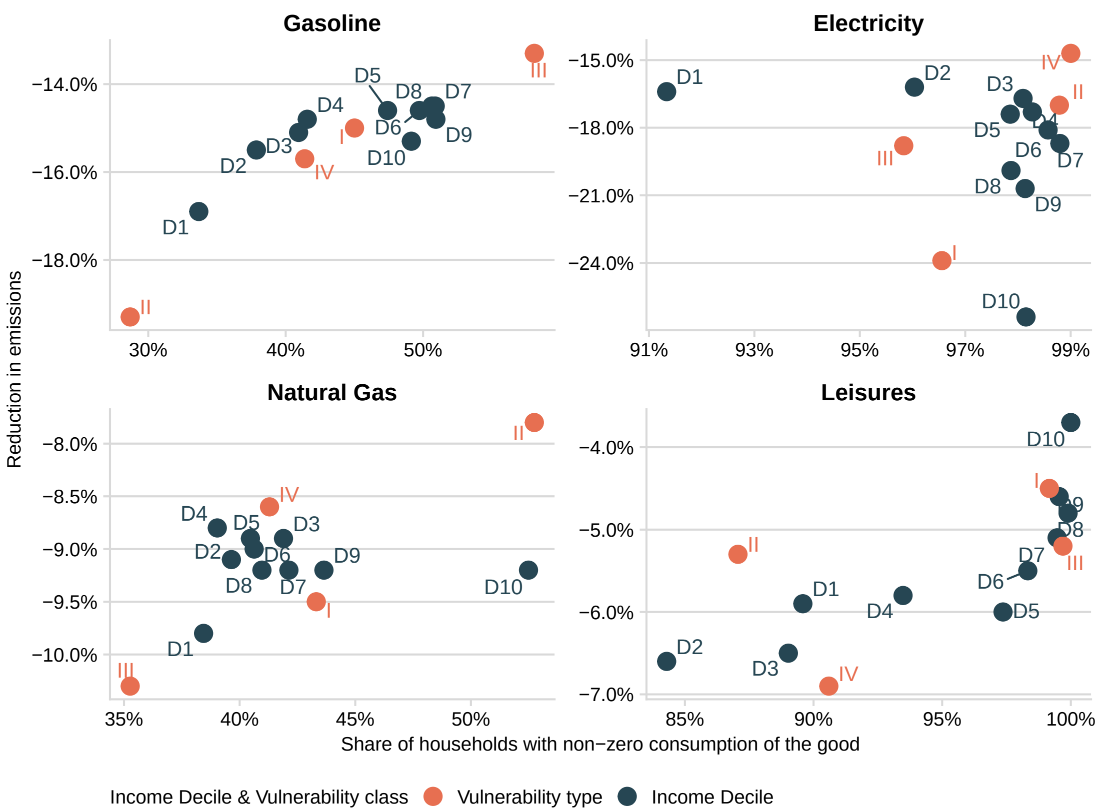
Our analysis highlights the impact of the carbon tax across households' characteristics that are not income. Variability between types of vulnerability — created as an artefact of elasticities estimation (see section 2.2) —- is greater than the variability between income deciles. As expected, type III households (dominated by urban working households) show high dependency on gasoline but large reduction in natural gas consumption. Conversely, type II households (low-income urban elderly households) favour heating over mobility and leisure, which translates in low reduction in natural gas and electricity but high reduction in gasoline.

Long-term price and income elasticities approximate the reaction of households to carbon price. Adaptation can be of three kinds: i) a reduction in consumption

[20] Respondents typically complete their shopping diaries over one or two weeks depending on the goods. For some goods this may lead to some variability if purchases are made less frequently than the response period. For summing up the expenditure this does not have so much impact as it averages the expenditure over large categories, overestimating the consumption of one household and overestimating that of the other. On a large enough sample the average consumption is quite correct. If a household consumes about €50 of fuel every week but only refills every fortnight, then a one-week survey will give a correct estimate of the aggregate consumption per week, i.e. €100. If we want to estimate the share of households experiencing backfire or being compensated for the carbon tax paid then we risk overestimating the backfire if both households are given the same lump-sum transfer. The first household, which is heavily taxed because it is a large consumer, will nevertheless reduce its consumption, but this will not be compensated by the lump-sum. Conversely, we consider that the second household does not consume any petrol and that part of the cash transfer will be spent on fuel. So we will consider that 50% of the sample will increase the emissions linked to fuel whereas, compared to their actual weekly consumption, it is possible that either they both increase their fuel emissions or they both decrease it. To reassure ourselves that our estimate is nonetheless accurate we need more assumptions: the frequency of purchase of carbon-intensive goods is higher than the duration of the survey, an average can be made on other carbon purchases, the behaviour of the poorest will be lower and more regular purchases. For electricity and gas consumption, annual or monthly bills are collected during the survey.

[21] 9.8% of expenditures for D1 household with non-zero fuel bills and 5.4% for D1 households owning a vehicle.

Figure 1.4 – Vertical and horizontal heterogeneity of emission reduction and user distribution



Note: The four vulnerability types are used in the estimation of elasticities. We have highlighted the most represented characteristics profile for each type: Type I: Young working class households tenants in large cities or in Paris (medium income deciles); Type II: isolated elderly households with low-income tenants in large cities; Type III: Working households with higher standards of living owning their homes in small towns; Type IV: elderly households owning their home in rural areas (low to medium income deciles).

by reducing waste, ii) investment in more energy-efficient appliances or dwellings, iii) or deprivation resulting in a loss of comfort. Similar studies undergone on French population at the same date (2010-2011) show that low-income households are already in a situation of deprivation of energy for space heating (Cayla et al., 2010). Low-income households are found among those most willing to reduce energy consumption but declare that they cannot invest in energy-efficient equipment that would allow them to decrease energy bills (Cayla et al., 2011; Bartiaux, 2006). Poorest households are particularly constrained in their access to capital, which is economically translated as high discount rate for energy efficient investment (Jaffe and Stavins, 1994). Therefore, it seems reasonable to conclude that the significant decrease in real energy consumption undergone by the first income deciles is mainly deprivation rather than investment in energy-efficient appliances.

From this section, we may draw two conclusions. Firstly, we conclude that carbon taxation is regressive in France. Despite limitations in our microsimulation — namely the absence of input-output model to compute the prices taking into account the production sector structure — it appears essential to couple carbon taxation with an appropriate redistribution policy. Secondly, the heterogeneity of carbon-intensive consumption will make the targeting of the carbon tax revenues recycling mechanism all the more important. If policymakers want to compensate each and every household in the first income decile, they would have to over-compensate the non-gasoline consumer in order to compensate the burdened households. It would likely trigger a large backfire effect for these households.

5.2 Between income and backfire effects

In this section, we present the consequences of the recycling of carbon tax revenues in the form of an equal per capita lump-sum transfer.[22] The overall reduction in emissions is of 5.9%, to be compared to the fall of 10.9% when we supposed the absence of recycling. We conclude that there is no full backfire effect, in the sense that a lump-sum rebated carbon tax still allows for a decrease in emissions.

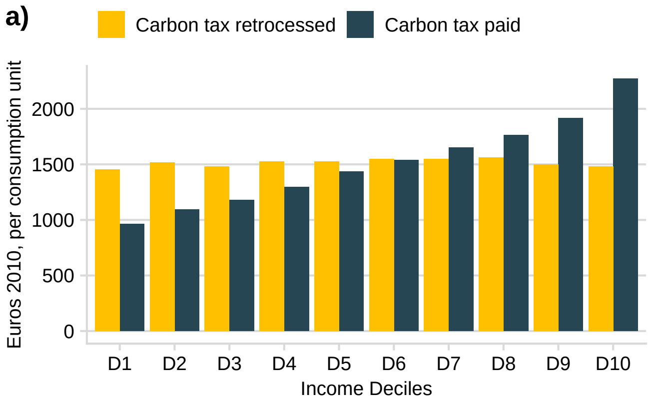
We detail how households use this additional income. We test alternative recycling mechanisms and the robustness of this result in the next section.

Distribution of the income effect

The carbon tax is made strongly progressive by an equal per capita lump-sum transfer since it benefits more the poorest households in proportion to their income. Because income inequalities are greater than inequalities in emissions, the transfer offsets the regressivity of the carbon tax. The lump-sum per capita of the carbon tax of 158€/tCO_2 amounts to 985€ per consumption unit (constant 2010 euros), i.e. an average extra income of 3.1%. It represents an extra-income of 10.2% for the D1 and 1.3% for

[22] It is more precisely per consumption unit lump-sum transfer, adapted with the OECD equivalence scale to take into account the size of the household, but we call hereafter per-capita transfer.

Figure 1.5 – Distribution of rebates among households



b)

Income Decile	Overcompensated households
1	82.4%
2	77.9%
3	72.6%
4	69.9%
5	62.2%
6	56.8%
7	51.7%
8	50.8%
9	39.1%
10	29%

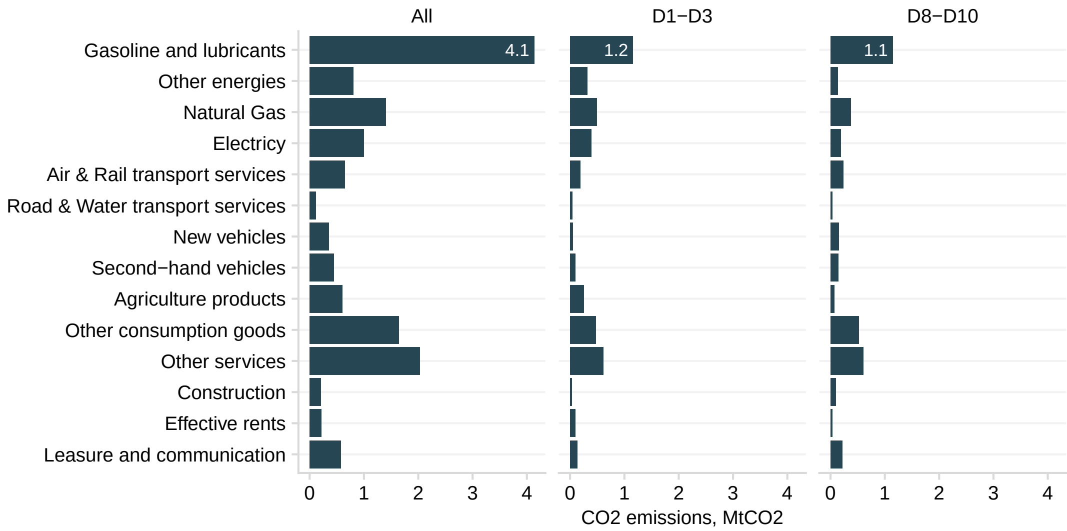
Note: (a) Carbon tax rebate and carbon tax bills aggregated per income decile and (b) the share or households for which the rebate compensates at least the carbon tax they are paying, which mean they are "over-compensated".

the D10. On average, the carbon tax benefits households below the median wage (D1-D5) who are compensated more than they pay in carbon tax. Again, the situation is heterogeneous, with the lump-sum compensating only 72% of D1-D5 households, ranging from 82.4% of D1 to 62.2% of D5 (Figure 1.5).[23]

Figure 1.6 shows how the increase and decrease of emissions (and therefore real consumption) are distributed among goods. All households mainly use the revenue from the carbon tax to buy back some of the gasoline they renounced because of the tax. The poorest households, D1-D3, use the lump-sum rebate to increase their energy consumption, including electricity. Their consumption of natural gas even exceeds the pre-tax level. They also increase their spending on food, leisure and other goods and services (composite goods). In contrast, wealthier households, D8-D10, spend less of their lump-sum rebate on food and energy (and almost none on electricity). However, they also increase their consumptions of leisure and other goods and services. All households increase their consumptions of rail and air transport services (these expenditures are aggregated, which is a limitation of the nomenclature because their carbon footprints are very different although they are quite similar in purpose). These results reflect quite directly the profile of income elasticities presented in section 4: income elasticities for food and electricity fall for high incomes, and are relatively stable and high for composite goods, recreation, travel and gasoline.

[23] We shall bear in mind that the 18% of D1 households who pay more carbon tax than the rebate may be households that have made a large expenditure of carbon goods (e.g. a significant refuel of gasoline) in the data collection period).

Figure 1.6 – Distribution of the lump-sum transfer per item



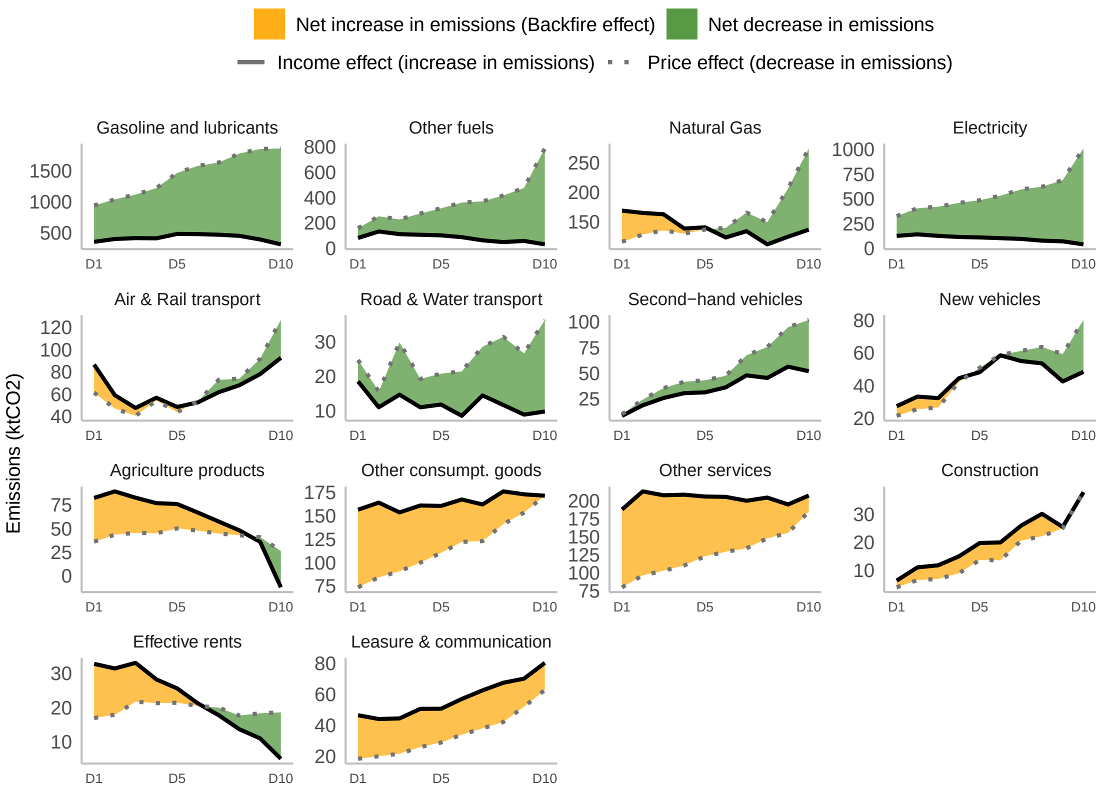
Backfire effect

Aggregate emissions are reduced by the tax even when accounting for the income effect of recycling carbon tax revenues. The allocation of a large share of the recycling revenues to gasoline does not fully offset the impact of the price signal. Figure 1.7 compares the price and the income effects for all items and income deciles. A backfire — i.e. a volume of emissions that exceeds the pre-tax level — arises when the income effect offsets the price effect (yellow area). With the exception of natural gas, whose consumption increases for the first half of the income distribution, the items for which there is a backfire are the least carbon-intensive items. The backfire magnitude decreases with income, it disappears at D5 for air and rail transport, new vehicles, food and rent.

The reduction of aggregate emissions is largely borne by high income deciles, both in volume (Figure 1.7) and relative to pre-tax emissions (Figure 1.8). Figure 1.8 represents the reduction in emissions due to the signal against the increase due to the income effect for the 14 goods of 40 classes of households (income deciles × vulnerability type). Any point higher than the black diagonal line indicates a backfire effect for a specific item. Adding horizontal heterogeneity of preferences, we find a stronger backfire effect for low- and middle-income households. However, the main message remains: the backfire is mostly located on low carbon-intensive goods and for households below the median income. D8-D10 households reduce their gasoline consumptions by almost 40% while the income effect is only about 3%. The level of consumption of the high-income — even the urban rich — is high enough that the income effect is insufficient to create a backfire on the most polluting goods.

Aggregate emissions decrease by 5.9% but D1 only reduces its emissions by 3.0% and D10 by 8.2%. About half (54%) of the D1 households experience a backfire effect

Figure 1.7 – Price and income effects per item and income decile



and increase their emissions relative to pre-tax levels, when it is only the case for 10.3% of D9 and 3.5% of D10 households (Figure 1.9). The latter households are mostly city dwellers and single households.[24]

Overall, about 25% of households increase their emissions after the tax and its recycling, mainly in D1-D5 households. Income effect for D1 represents 1.4MtCO_2 (Figure 1.9), which amounts to 3.5% of D10 emissions after tax and recycling. The whole D1-D3 income effect (4.4 MtCO_2) only weighs 11% of D10 emissions. We already have the intuition — before testing it in the next section — that the way to increase the effectiveness of the tax without compromising fairness is not to reduce the income effect of the poorest but to increase the effort of the richest.

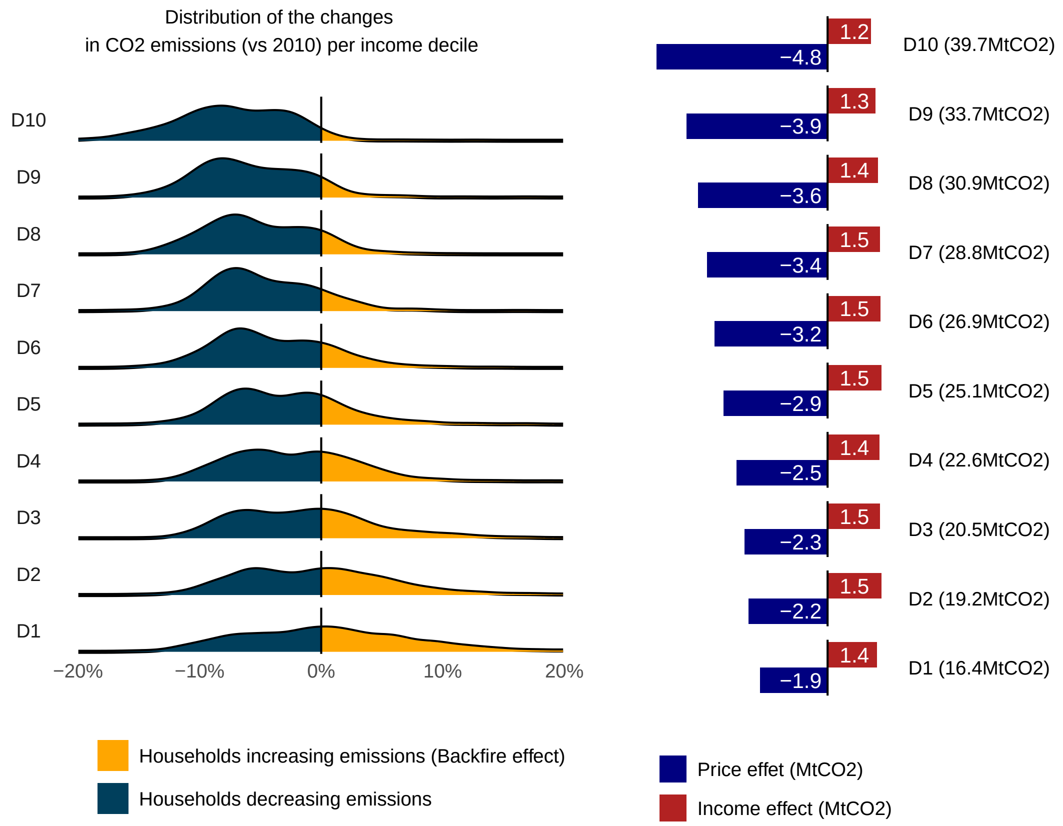
Figure 1.10 crosses income with other horizontal dimensions and shows for each cell the share of households experiencing a backfire effect. Households whose emissions increase compared to pre-tax levels, beyond the key dimension of income, are always the

[24] A possible explanation for D10 households with emissions low enough that they experience a backfire would be that these households have only *seasonally* low emissions. BDF addresses the seasonality issue by conducting its survey in 6 waves spread over 12 months. Backfire households are not significantly more present in any of the 6 survey waves. See Figure 1.C.5, appendix 1.C.3.

Figure 1.8 – Price and income effects of consumption over the 40 cells of households (income deciles × vulnerability types) for the 14 goods and services of the frameworks represented by their carbon intensity

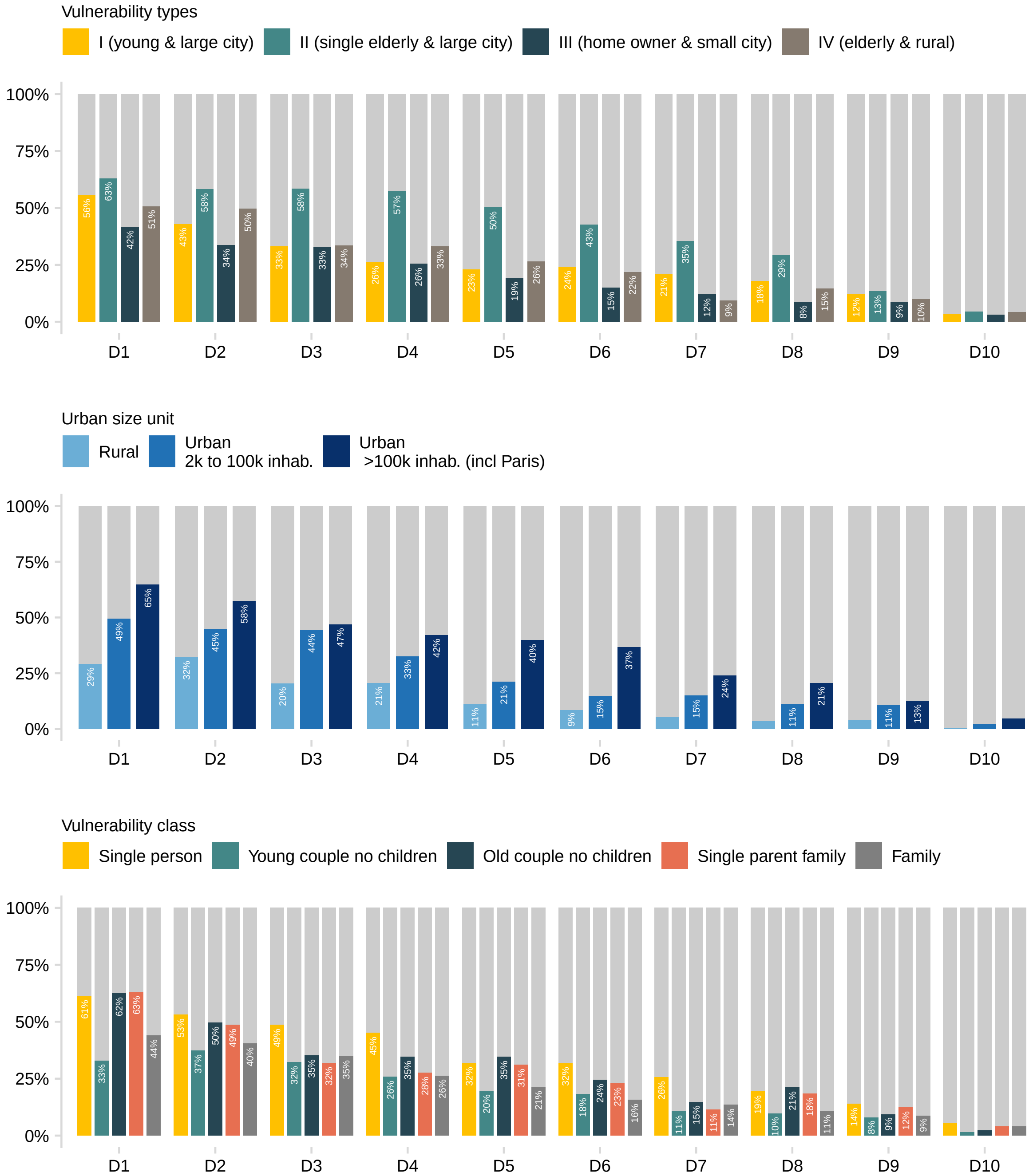
Note: For each of 14 goods, the decrease in real consumption due to the carbon tax ("Price effect") is compared to the increase in consumption following the lump-sum transfer. Both variations are vis-à-vis no-policy consumption. Hence, a backfire effect exactly compensating the price effect would be situated in the black line. All points above this line are increased consumption due to the carbon tax and its recycling. Size of point indicates the carbon intensity of the particular good.

Figure 1.9 – Carbon tax and recycling: backfire of CO_2 emissions per income decile



Source: Authors calculations. Reading: Almost half of the households in D1 increase their emissions after the introduction of the tax and its recycling by equal per capita lump-sum transfer: there is a backfire effect. But for D1 the increase in emissions due to the recycling amounts to 1.4 $MtCO_2$, that is, 3.5% of the emissions of D10. The optimal solution is to focus the recycling on the first deciles. Comments: The first panel represents the distributional density of household emissions increases or decreases relative to 2010 broken down by income deciles. The densities are adjusted to the number of households represented. The second panel represents the change in aggregate emissions of the decile due to the price signal of the tax and the income effect of the recycling of the carbon tax revenues.

Figure 1.10 – Share of households experiencing a backfire effect in emissions per income decile and another horizontal dimension



Note: Share of households with a backfire effect. Values below 6% do not appear on the graph.

Table 1.1 – Impact of the carbon price on the reduction of emissions

Carbon price (€/tCO2)	Price signal (emissions vs 2010) (A)	Price & income effects (emissions vs 2010) (B)	Partial backfire (ratio of the two effects) (B/A-1)
10	-0.7%	-0.4%	-47.1%
50	-3.7%	-1.9%	-47.0%
100	-7.1%	-3.8%	-46.6%
150	-10.4%	-5.6%	-46.2%
200	-13.6%	-7.4%	-45.7%
300	-19.5%	-10.8%	-44.6%
400	-25.0%	-14.3%	-43.0%
500	-30.2%	-17.8%	-41.0%
750	-42.0%	-27.5%	-34.6%
1000	-53.0%	-39.0%	-26.4%

most urban and the oldest. This makes them the most fuel elastic as they have access to better public transport and in the case of retired households have little forced mobility because they escape daily commuting. The influence of vulnerability type varies with income. Type II (urban elderly) contains significantly more backfire households for D3-D8 than other types. It is not the case for extreme income deciles. Similarly, single households stand out from D3 onwards, while they compare with single-parent families and old couples for D1-D2.

5.3 Extensions

In this section, we extend the previous work in several directions and test for more policy designs.

Increasing the carbon price

We compute the reduction in emissions for several values of the carbon tax. Final emission reductions versus 2010 — including the recycling of carbon tax revenues on an equal per capita lump-sum transfer — are almost linearly related to the value of the carbon tax. Nevertheless, the magnitude of the backfire effect decreases as the carbon tax increases (Table 1.1). At 158€/tCO_2 a little less than half of the decrease in emissions due to the price signal is offset by the income effect. The proportion is only 25% for a 1000€/tCO_2 tax. The ratio of emissions reduction after and before the rebate increases with the price of carbon. It means that the full taxation & recycling mechanism is more and more effective as the policy is more ambitious.

Table 1.2 – Reduction in aggregate emissions without vertical heterogeneity of preferences

Decile preference generalised to total population	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
Aggregate emissions (vs 2010)	-5.75%	-5.36%	-5.32%	-5.61%	-5.38%	-5.75%	-5.92%	-6.32%	-6.44%	-8.22%

Reading: If all households were to behave as D1 households aggregate reduction in emissions would be -5.75%.

Homogenising preferences

We run several simulations where we assume greater homogeneity of preferences of households. We test for the absence of vertical heterogeneity, by allowing all households to react using the elasticities of the D10, according to their vulnerability type, *as if they were rich*. The overall reduction in emissions would then be -8.2%, that is 2.3pts lower than the simulation with full heterogeneity of preferences. Table 1.2 summarises the reduction if each income deciles preferences were to be applied to all households. Without surprise, D10 preferences are those allowing the largest emissions reduction due to high price elasticities. The behaviour of the low- and middle-income deciles drive emissions up compared to the baseline.

If everyone acted like a D1 household, there would be little difference on aggregate emissions because two mechanisms would compensate each other: the middle classes (D2-D7) which have lower price elasticities in absolute terms would reduce their emissions more, but the richest, who are normally more elastic, would therefore reduce their emissions less (by 1.8 pts: D10 with D1 elasticities cut their emissions by 6.4% instead of 8.2% with their own elasticities).

Likewise, if we suppose horizontal homogeneity, emissions will decrease more if all households are type I and II (resp. -6.79% and -7.41% in emissions versus 2010). These types are dominated by urban households which are much less dependent on gasoline and thus exhibit higher price elasticities.

We may conclude that heterogeneity of preferences may either boost or slow down emissions reduction. Differentiating the behaviour of low-income deciles and rural households is key to avoiding overestimating the reduction of emissions.

Focusing the recycling mechanism

The equal per capita lump-sum allows the carbon tax to be progressive across income deciles. Surveys show that public support for the carbon tax is highest when the recycling of its revenues is earmarked for green investments or recycled and targeted at low-income households (Dechezleprêtre et al., 2022).[25]

[25] Ewald et al. (2022) finds that recycling the carbon revenues to households, either to the low-income or to all, is not popular in Sweden, unlike using the revenues to invest in clean energy and research on climate change.

Table 1.3 – Emissions reduction with targeted recycling of the full carbon tax revenues on the first income deciles

D1-D10	D1-D9	D1-D8	D1-D7	D1-D6	D1-D5	D1-D4	D1-D3	D1-D2	D1
-5.90%	-5.82%	-5.77%	-5.71%	-5.69%	-5.66%	-5.68%	-5.63%	-5.67%	-5.76%

Reading: Carbon tax 158€/tCO_2 . The full carbon tax is recycled towards the households indicated in the form of an equal per capita lump-sum transfer. Recycling the 41 billion euros to the first income brings an emissions reduction of 5.76%.

Table 1.4 – Emissions reduction with equal per capita lump-sum recycling restricted to the first income deciles

D1-D10	D1-D9	D1-D8	D1-D7	D1-D6	D1-D5	D1-D4	D1-D3	D1-D2	D1
-5.90%	-6.35%	-6.84%	-7.36%	-7.89%	-8.42%	-8.95%	-9.46%	-9.97%	-10.48%

Reading: Carbon tax 158€/tCO_2 . The rebate per consumption unit is 985€ in all the recycling mechanisms. Only the indicated income deciles actually perceived the rebate. The remaining carbon tax revenues is earmarked for green investments that we suppose not carbon-emitting. Restricting the carbon tax revenues to the first 9 income deciles, excluding the top 10%, means a reduction in aggregate emission of 6.35% compared to -5.90% if the D10 is included.

To target low-income households, we exclude the richest households from the recycling mechanism. The full carbon tax revenues are then given back in the form of a larger equal per capita lump-sum transfer to the first income deciles. Whatever the households benefiting from this targeted mechanism, the emission reduction is almost the same (Table 1.3). We conclude that to reduce emissions further, we need to downsize the share of carbon tax revenues redistributed to households. This would kill one bird with two stones and free up revenue that could be earmarked for investments in low-carbon technologies or subsidies directed to households for thermal renovation or electric vehicles, for instance.

Emissions are further reduced if the mechanism excludes the top income deciles without increasing the rebate for the rest of the population (Table 1.4). If 50% of the carbon tax revenues is recycled towards the bottom half of the income distribution (with a similar 985€ per consumption unit), aggregate emissions are reduced by 8.4%. Cutting the recycling for the top 40% means improving the effectiveness of the tax by 2 points, to -7.9% on emissions. There is therefore a trade-off between reducing emissions further and offsetting as many households as possible.

Policymakers can then try to achieve a certain emission reduction target. If we assume that the objective is that the income effect should not offset more than 25% of the emission reduction due to the price signal (arbitrary example), from the Table 1.4 we infer that only 60% of the amount of the tax should be recycled. Indeed, we have seen that it is the amount of tax recycled that influences emissions more than its distribution (Table 1.3)

Figure 1.11 illustrates the trade-off between the emission target and progressivity. Two mechanisms are compared: i) an equal per capita lump-sum spread over D1-D6, D1-D8 or D1-D10, and ii) a mechanism skewing the redistribution towards low-income households. If n deciles are included in the recycling, then a household in D1 will receive n times more per capita than a household in Dn; a household in D2, $n-1$ times more, etc. This mechanism may not be optimal but it illustrates how a recycling mechanism can focus on the lowest incomes.

The reduction in emissions is comparable between all mechanisms. What changes is the progressivity of the net carbon tax, the share of D1 households fully compensated of their carbon tax bill and the share of households that increase their emissions (experiencing a backfire). We should then focus on the distributional aspects.

First, recycling 60% of the tax revenue on an equal per capita basis to all households makes the tax progressive but does not fully compensate the top deciles on average. A mechanism that excludes the top deciles creates a large increase in the weight of carbon tax relative to income for the last income deciles. It risks threatening acceptability.

Mechanisms favouring low-income households allow for better progressivity, by slightly compensating the richest. The trade-off is between 3 dimensions: progressivity, the protection of D1 households and the share of individual backfire effects.

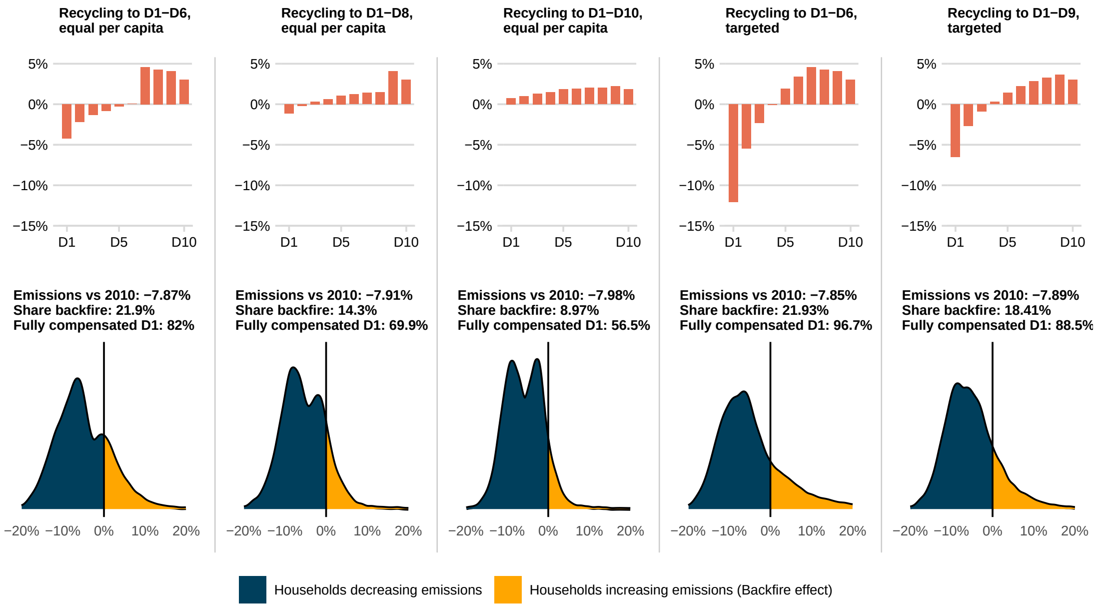
These mechanisms increase the share of D1 households that are at least compensated for their carbon bill. If recycling is targeted and limited to D1-D6, 99.7% of D1 is at least compensated, compared to 88.5% if D1-D9 are compensated (targeted), and only 69.9% with an equal per-capita on D1-D8. In a targeted mechanism, however, households in D4-D5 are not compensated on average (the distribution is too skewed towards low-income households). If the share of fully compensated D1 households and the share of backfire households are correlated, the equal per capita lump-sum transfers to D1-D6 (column 1) and the targeted recycling towards D1-D6 (column 4) allow about 22% of households to increase their emissions, but fully compensate respectively 82 and 96% of D1 households.

6 Conclusion

This chapter assesses the long-term reduction in emissions induced by a carbon tax whose revenues are recycled to households. We find that a backfire effect — an increase of aggregate emission above the pre-tax level — can theoretically take place but that in France, the recycling of carbon tax revenues only offsets about half of the emissions reduction.

We used a partial equilibrium set-up to derive the conditions for the carbon tax and lump-sum recycling to decrease aggregated emissions. We estimated price and income elasticities for 14 expenditure items for 40 classes of households using 1979-2010 French Household Budget surveys. We developed a microsimulation model to assess emissions reductions and distributional impacts of the carbon tax and its revenue recycling mechanism.

Figure 1.11 – Equity versus effectiveness with recycling 60% of the carbon tax revenues to households



Note: Each column corresponds to a recycling mechanism of the carbon tax revenues. In all mechanisms, only 60% of the total amount of carbon tax revenues is redistributed to households. The figure compares a recycling mechanism on the progressivity of the tax, emissions reduction, the share of individual backfires and the share of fully compensated D1 households. The so-called "targeted" mechanisms recycle over n income deciles (D1Dn) and are biased in favour of the poorest, giving n times more to D1 than to Dn. A negative net tax indicates that the decile's recycling revenue is higher than its tax payments The lower graph plots the density of the emission reduction among all households. One part of the households (yellow) increases its emissions above the pre-tax level, another part (navy blue) reduces its emissions.

We show with a simple model that there is a risk of backfire due to recycling carbon tax revenues. In France, the most energy-intensive households are the low-income ones. The recycling mechanisms will therefore compensate these households and transfer the carbon tax revenues from the richest to the poorest. Low-income households are also the least price elastic for natural gas and electricity, and the most income elastic for these same goods. Conversely, middle-income households rather than low-income ones are the most dependent on fuel. We show that horizontal heterogeneity has a large impact on the elasticities of energy goods: rural households are less price elastic on gasoline, while older households are less price elastic on natural gas and electricity for heating.

Overall, a carbon tax of 158€/tCO_2 — which was the level of carbon tax planned in France for 2025 before the freeze that followed the *Gilets Jaunes* protests — recycled at 100% to households in the form of an equal per capita (on an equivalence scale) lump-sum transfer reduces aggregate emissions by 5.9%. Recycling 60% of the carbon tax revenues only leads to emissions reduction of about 8%: the income effect is only a quarter of the price effect. Depending on the recycling mechanism, more or less targeted towards low-income, the reform backfires for 9% to 22% of households, who increase their emissions above the pre-tax level depending on their location (urban or rural), their age and the type of dwelling they live in.

We conclude that although it is a valid concern that the recycling of the carbon tax revenues partially offsets the tax-induced reduction in emissions, the limited backfire effect is not sufficient to prevent any compensation for the low-income households in the name of emissions reduction. If the recycling is partial and targeted towards the lower income groups (for instance, excluding the richest 20% of households D9-D10 and skewed towards the first income deciles), it makes the tax progressive. It is then up to policymakers to fine-tune the recycling mechanism to maximise social acceptability according to citizens' preferences for a progressive tax, protection of the poorest or more equitable distribution of the emission reduction effort.

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Appendix

- Qu'est-ce que c'est que la justice ?
– Jamais entendu parler, dit le chef de production. J'ai du travail, il faut dire.

Boris Vian, *L'écume des jours*

1.A Theoretical model

1.A.1 A single household with a single polluting good

Program

$$\begin{cases} E_1 = E_0(1+\varepsilon_p^E \eta_E t)\left(1+\varepsilon_r^E \dfrac{S}{E_0+X_0}\right) \\ X_1 = X_0\left(1+\varepsilon_r^X \dfrac{S}{E_0+X_0}\right) \\ S = E_1 \eta_E t \end{cases} \tag{1.20}$$

The solutions of this system are:

$$\begin{cases} X_1 = X_0 \dfrac{1-(\varepsilon_r^E-\varepsilon_r^X)\dfrac{E_0}{B_0}\eta_E t(1+\varepsilon_p^E\eta_E t)}{1-\varepsilon_r^E\dfrac{E_0}{B_0}\eta_E t(1+\varepsilon_p^E\eta_E t)} \\ E_1 = E_0 \dfrac{\dfrac{E_0}{B_0}(1+\varepsilon_p^E\eta_E t)}{1-\varepsilon_r^E\dfrac{E_0}{B_0}\eta_E t(1+\varepsilon_p^E\eta_E t)} \end{cases} \tag{1.21}$$

with $B_0 = X_0 + E_0$.

Hypotheses We assume throughout this exercise that price and income elasticities allow for balanced household budgets by keeping savings constant (see discussion of our elasticities in section 3):

$$X_0 + E_0 = E_1 + X_1 \tag{1.22}$$

The fact that we do not derive situation-specific elasticities prevents us from imposing that the elasticities sum to 1 for each item i:

$$\begin{cases} 1 = \sum_i w_0^i \left(1 + \varepsilon_p^i \frac{\Delta p^i}{p_0^i}\right) \\ 1 = \sum_i w_0^i \varepsilon_r^i \end{cases}$$

Ensuring these conditions are always met while solving (1.20) would mean that consumers define their preferences (i.e. their elasticities) at the same time as their consumption, which is absurd and moreover violates the utility maximisation at the basis of demand systems. We derive elasticities from a budget-constrained household utility maximisation programme, which assumes consumption-independent elasticities. Therefore, in the microsimulation part of this chapter, we ensure that budgets are balanced by iteration.

We ensure the budget is balanced ex-post, $B_1 = B_0$. Which is the same as writing:

$$E_0 \sigma \eta_E t \left(\varepsilon_p^E + (1 + \varepsilon_p^E \sigma \eta_E t)\left(\varepsilon_r^E \frac{E_0^p}{E_0^p + X_0^p} + \varepsilon_r^X \frac{X_0^p}{E_0^p + X_0^p}\right)\right) = 0 \tag{1.23}$$

The first term, $E_0 \sigma \eta_E t \varepsilon_p^E$, indicates how much the energy budget has decreased and the second term the increase following the rebate.

We also impose that even in the absence of recycling, expenditure remains positive, i.e.

$$1 + \varepsilon_p^E \eta_E t > 0 \tag{1.24}$$

Emissions reduction The growth rate of emissions is:

$$\frac{\chi_1}{\chi_0} - 1 = \frac{\eta_E t \left(\varepsilon_p^E + \frac{E_0 \varepsilon_r^E}{B_0}(1 + \varepsilon_p^E \eta_E t)\right)}{1 - \frac{\varepsilon_r^E E_0^p \eta_E t}{B_0}(1 + \varepsilon_p^E \eta_E t)}, \tag{1.25}$$

with $\chi_0 = E_0 \eta_E$ et $\chi_1 = E_1 \eta_E$.

The denominator of this equation is always positive, otherwise no matter how much S is recycled, the carbon tax generated by this extra revenue would be greater than S: we would have an infinite cycle.

It can also be seen as:

$$\text{If } 1 - \frac{\varepsilon_r^E E_0^p \eta_E t}{B_0}(1 + \varepsilon_p^E \eta_E t) < 0,$$

then

$$\forall S > 0,\ \frac{W\varepsilon_r^E E_0^p \eta_E t}{B_0}(1+\varepsilon_p^E \eta_E t) > S,$$

and since

$$S = \eta_E t E_0(1+\varepsilon_p^E\eta_E t) + \eta_E t E_0(1+\varepsilon_p^E\eta_E t)\left(\varepsilon_r^E \frac{S}{E_0+X_0}\right),$$

then if the second term is greater than S, the first term must be negative to balance, which is impossible since all of the components of the first term are positive.

The sign of the growth rate of emissions is therefore driven by the numerator of the expression. Intuitively, this ratio is positive when the income effect is weaker than the price effect. Mathematically, it means that:

$$\varepsilon_p^E + \frac{E_0\varepsilon_r^E}{B_0}(1+\varepsilon_p^E\eta_E t) < 0. \tag{1.26}$$

Given that

$$\varepsilon_p^E + (1+\varepsilon_p^E\eta_E t)\left(\varepsilon_r^E\frac{E_0}{B_0}\right) + (1+\varepsilon_p^E\eta_E t)\left(\varepsilon_r^X\frac{X_0}{E_0+X_0}\right), \tag{1.27}$$

it would mean that we have the following:

$$(1+\varepsilon_p^E\eta_E t)\left(\varepsilon_r^X\frac{X_0}{B_0}.\right) < 0 \tag{1.28}$$

Equation (1.28) is impossible to achieve since the price effect cannot be greater than 100%, hence:

$$(1+\varepsilon_p^E\sigma\eta_E t) \geq 0$$

and of course:

$$\varepsilon_r^X\frac{X_0}{B_0} \geq 0.$$

The conclusion is that we always have a decrease in emissions given these hypotheses.

1.A.2 A single household with two polluting goods

Program

$$\begin{cases} E_1 = E_0(1+\varepsilon_p^E\eta_E t)\left(1+\varepsilon_r^E\frac{S}{E_0+X_0}\right) \\ X_1 = X_0(1+\varepsilon_p^X\eta_X t)\left(1+\varepsilon_r^X\frac{S}{E_0+X_0}\right) \\ S = E_1\eta_E t + X_1\eta_X t \end{cases} \tag{1.29}$$

The solutions of this system are:

$$\begin{cases} X_1 = X_0 \dfrac{(1+\varepsilon_p^X \eta_X t)(-1+(\varepsilon_r^E-\varepsilon_r^X)\dfrac{E_0}{B_0}\eta_E t(1+\varepsilon_p^E\eta_E t)}{1-\varepsilon_r^E\dfrac{E_0}{B_0}\eta_E t(1+\varepsilon_p^E\eta_E t)-\varepsilon_r^X\dfrac{X_0}{B_0}\eta_X t(1+\varepsilon_p^X\eta_X t)} \\ E_1 = E_0 \dfrac{(1+\varepsilon_p^E \eta_E t)(1+(\varepsilon_r^E-\varepsilon_r^X)\dfrac{X_0}{B_0}\eta_X t(1+\varepsilon_p^X\eta_X t)}{1-\varepsilon_r^E\dfrac{E_0}{B_0}\eta_E t(1+\varepsilon_p^E\eta_E t)-\varepsilon_r^X\dfrac{X_0}{B_0}\eta_X t(1+\varepsilon_p^X\eta_X t)} \end{cases} \tag{1.30}$$

with $B_0 = X_0 + E_0$.

Emissions growth rate

$$\frac{\chi_1}{\chi_0}-1 = \frac{\left(\varepsilon_p^E\eta_E^2 t E_0 + (1+\varepsilon_p^E\eta_E t)\chi_0\dfrac{\varepsilon_r^E E_0\eta_E t}{B_0}\right)+\left(\varepsilon_p^X\eta_X^2 t X_0 + (1+\varepsilon_p^X\eta_X t)\chi_0\dfrac{\varepsilon_r^X X_0\eta_X t}{B_0}\right)}{1-\dfrac{\varepsilon_r^E E_0\eta_E t}{B_0}(1+\varepsilon_p^E\eta_E t)-\dfrac{\varepsilon_r^X X_0\eta_X t}{B_0}(1+\varepsilon_p^X\eta_X t).} \tag{1.31}$$

The effects add up linearly to the case where $\eta_X = 0$, but unlike section 1.A.1, the solutions are symmetrical in X and E.

1.A.3 Transfers between households

Program The program of consumption at time 1 is:

$$\begin{cases} E_1^P = E_0^P(1+\varepsilon_p^E\eta_E t)\left(1+\varepsilon_r^E\dfrac{xS}{E_0^P+X_0^P}\right) \\ X_1^P = X_0(1+\varepsilon_p^X\eta_X t)\left(1+\varepsilon_r^X\dfrac{xS}{E_0^P+X_0^P}\right) \\ E_1^R = E_0^R(1+\varepsilon_p^E\eta_E t)\left(1+\varepsilon_r^E\dfrac{(1-x)S}{E_0^R+X_0^R}\right) \\ X_1^R = X_0^R(1+\varepsilon_p^X\eta_X t)\left(1+\varepsilon_r^X\dfrac{(1-x)S}{E_0^R+X_0^R}\right) \\ S = (E_1^P+E_1^R)\eta_E t + (X_1^P+X_1^R)\eta_X t \end{cases} \tag{1.32}$$

NB: solutions to this system are not digest and add little to the understanding of the problem at hand.

Emissions growth rate

$$\frac{\chi_1}{\chi_0} - 1 = \left[\chi_0^E \eta_E \varepsilon_p^E \eta_E t + \chi_0^X \eta_X \varepsilon_p^X \eta_X t + \chi_0 \varepsilon_r^E \eta_E t(1 + \varepsilon_p^E \eta_E t)\left(x\frac{E_0^P}{B_0^P} + (1-x)\frac{E_0^R}{B_0^R}\right) + \chi_0 \varepsilon_r^X \eta_X t(1 + \varepsilon_p^X \eta_X t)\left(x\frac{X_0^P}{B_0^P} + (1-x)\frac{X_0^R}{B_0^R}\right)\right] / \left[1 - \varepsilon_r^E \eta_E t(1 + \varepsilon_p^E \eta_E t)\left(x\frac{E_0^P}{B_0^P} + (1-x)\frac{E_0^R}{B_0^R}\right) - \varepsilon_r^X \eta_X t(1 + \varepsilon_p^X \eta_X t)\left(x\frac{X_0^P}{B_0^P} + (1-x)\frac{X_0^R}{B_0^R}\right)\right] \quad (1.33)$$

As in appendix 1.A.1, the denominator of the expression (1.33) is always positive because the budget is balanced.

Derivative of the growth rate of emissions relative to x, the carbon tax revenues allocation

$$\frac{\partial\left(\frac{\chi_1}{\chi_0} - 1\right)}{\partial x} = \left[\left(\varepsilon_r^E \eta_E t(1 + \varepsilon_p^E \eta_E t) - \varepsilon_r^X \eta_X t(1 + \varepsilon_p^X \eta_X t)\right)(E_0^P X_0^R - E_0^R X_0^P)\left(\chi_0^E(1 + \varepsilon_p^E \eta_E t) + \chi_0^X(1 + \varepsilon_p^X \eta_X t)\right)\right] / \left[\chi_0\left(1 - \varepsilon_r^E \eta_E t(1+\varepsilon_p^E \eta_E t)\left(x\frac{E_0^P}{B_0^P} + (1-x)\frac{E_0^R}{B_0^R}\right) - \varepsilon_r^X \eta_X t(1+\varepsilon_p^X \eta_X t)\left(x\frac{X_0^P}{B_0^P} + (1-x)\frac{X_0^R}{B_0^R}\right)\right)^2\right] \quad (1.34)$$

The denominator of the fraction is always positive. We have imposed the following hypotheses,

1. $(1 + \varepsilon_p^E \eta_E t) > 0$,
2. $(1 + \varepsilon_p^X \eta_X t) > 0$, and
3. $\frac{E_0^P}{X_0^P} > \frac{E_0^R}{X_0^R}$, hence $E_0^P X_0^R - E_0^R X_0^P > 0$.

It stems that the sign of the numerator depends on the central term and on the following condition:

$$\varepsilon_r^X \eta_X(1 + \varepsilon_p^X \eta_X t) < \varepsilon_r^E \eta_E(1 + \varepsilon_p^E \eta_E t) \quad (1.35)$$

Growth rate of emissions when the full carbon tax revenues is recycled towards the energy-intensive household P: $x = 1$ The evolution of total emissions is given by:

$$\left(\frac{\chi_1}{\chi_0}-1\right) = \frac{\varepsilon_p^E \eta_E t \chi_0^E + \varepsilon_p^X \eta_X t \chi_0^X + \left(\varepsilon_r^X \frac{X_0^P}{B_0^P}\eta_X t(1+\varepsilon_p^X \eta_X t) + \frac{E_0^P}{B_0^P}\varepsilon_r^E \eta_E t(1+\varepsilon_p^E \eta_E t)\right)\chi_0}{\left(1-\frac{X_0^P}{B_0^P}\varepsilon_r^X \eta_X(1+\varepsilon_p^X \eta_X t) - \frac{E_0^P}{B_0^P}\varepsilon_r^E \eta_E(1+\varepsilon_p^E \eta_E t\right)\chi_0} \tag{1.36}$$

The denominator of this function is always positive to ensure a balanced budget (see appendix 1.A.1). The sign of this expression depends on the sign of the numerator: the two price effect terms ($\varepsilon_p^E < 0,\ \varepsilon_p^X < 0$) are negative, and the income effect terms are positive. It all depends on which effect prevails over the other, and there are multiple combinations.

Growth rate of emissions when the full carbon tax revenues is recycled towards the least energy-intensive household R: $x = 0$

$$\frac{\chi_1}{\chi_0}-1 = \frac{\chi_0^E \varepsilon_p^E \eta_E t + \chi_0^X \varepsilon_p^X \eta_X t + \chi_0\left(\varepsilon_r^E \eta_E t(1+\varepsilon_p^E \eta_E t)\left(\frac{E_0^R}{B_0^R}\right) + \varepsilon_r^X \eta_X t(1+\varepsilon_p^X \eta_X t)\left(\frac{X_0^R}{B_0^R}\right)\right)}{\left(1-\left(\frac{E_0^R}{B_0^R}\right)\varepsilon_r^E \eta_E t(1+\varepsilon_p^E \eta_E t) - \left(\frac{X_0^R}{B_0^R}\right)\varepsilon_r^X \eta_X t(1+\varepsilon_p^X \eta_X t\right)\chi_0} \tag{1.37}$$

1.B Elasticities estimates

1.B.1 Computation of elasticities

We present here the detailed calculations of the estimated elasticities on the 14 consumption items.

The computations of elasticities from the coefficients draw heavily on the article by Pawlowski and Breuer (2012) from which the following computations are derived with the results of Green and Alston (1990) for the popular LA-AIDS model.

Equation (1.17) above, relates the budget shares to the logarithms of real expenditure and the item price. In this specification, the coefficients are interpreted as budget share elasticities, and we wish to calculate the income and price elasticities of total expenditure.

In the case of equation (1.17), the elasticities are respectively for price and income:

$$
\begin{aligned}
e_{E_iP_i} &= \frac{\partial E_i}{\partial P_i}\frac{P_i}{E_i} = \frac{d_i}{w_i} - c_i \\
e_{E_iX} &= \frac{\partial E_i}{\partial X}\frac{X}{E_i} = 1 + \frac{c_i}{w_i}
\end{aligned}
\tag{1.38}
$$

For each good i, the simplified expression of the Engel curve is:

$$w_i = a_i + c_i \log\left(\frac{X}{P^*}\right) + d_i \log(P_i) + e_i \tag{1.39}$$

We voluntarily omit time t and the coefficients of the principal components without loss of generality. The coefficients are interpreted as semi-elasticities of the budget share to real expenditure (X/P^*) and to price P_i (Deaton and Muellbauer, 1980). Therefore, we need to find the expressions of the price and income elasticities of expenditure for each item as functions of the regression coefficients on price and income.

Consider the total expenditure:

$$X = \sum_{i=1}^{14} E_i \tag{1.40}$$

from which the budget shares are calculated:

$$w_i = \frac{E_i}{X} = \frac{E_i}{\sum_{i=1}^{14} E_i}. \tag{1.41}$$

The calculus trick consists mainly in using Engel's equation (1.39), noticing that

$$E_i = X \cdot w_i,$$

so that:

$$E_i = Xw_i = Xa_i + Xc_i \log\left(\frac{X}{P^*}\right) + Xd_i \log(P_i) \tag{1.42}$$

That is,

$$E_i = Xa_i + Xc_i \log(X) - Xc_i \log(P^*) + Xd_i \log(P_i) \tag{1.43}$$

A difficulty with equation (1.39) is that the Stone index P^*, is a function of individual prices P_i, which causes a simultaneity bias that makes the OLS estimator inconsistent. The model must therefore be estimated using instrumental variables but, above all, this relationship between the expenditure deflator and elasticities must be taken into account.

Consider the expression of the Stone index:

$$\log(P^*) = \sum_{i=1}^{14} w_i \log(P_i) \tag{1.44}$$

The derivative for any individual price i is:

$$\frac{\partial \log(P)}{\partial P_i} = \frac{w_i}{P_i} \tag{1.45}$$

We can now calculate the expression of $\partial E_i/\partial X$, i.e.:

$$\frac{\partial E_i}{\partial X} = a_i + c_i \log(X) - c_i \log(P^*) + d_i \log(P_i) + \frac{X c_i}{w_i} \tag{1.46}$$

Likewise, since we have $w_i = E_i/X$, it follows immediately that: $X/E_i = 1/w_i$. This allows us to deduce the expression of the income elasticity of the expenditure of item i:

$$\frac{\partial E_i}{\partial X} = w_i + c_i. \tag{1.47}$$

Hence, the income elasticity is:

$$e_{E_i X} = \frac{\partial E_i}{\partial X}\frac{X}{E_i} = (w_i + c_i)\frac{1}{w_i} = 1 + \frac{c_i}{w_i}. \tag{1.48}$$

For the price elasticity of expenditure of product i under consideration, the computation is similar although somewhat more complicated. Starting from equation (1.43), we compute the price elasticity for item i:

$$\frac{\partial E_i}{\partial P_i} = -X c_i \frac{\partial \log(P^*)}{\partial P_i} + \frac{X d_i}{P_i}. \tag{1.49}$$

Now, we recall the expression (1.45) and introduce it in (1.49):

$$\frac{\partial E_i}{\partial P_i} = -X c_i \frac{w_i}{P_i} + \frac{X d_i}{P_i}. \tag{1.50}$$

Let us now calculate the second member of the price elasticity expression,

$$\begin{aligned} e_{E_i P_i} &= \frac{\partial E_i}{\partial P_i} = \left(\frac{X d_i}{P_i} - X c_i \frac{w_i}{P_i}\right)\frac{P_i}{X w_i} \\ &= \frac{X d_i}{P_i} \times \frac{P_i}{X w_i} - \frac{X w_i c_i}{X w_i} \\ &= \frac{d_i}{w_i} - c_i \end{aligned} \tag{1.51}$$

Notice that if Engel's equation was more general using all prices or if we used a different deflator than the Stone index given by equation (1.44), the expressions of the elasticities would be different.

Table 1.B.1 – Aggregated price and income elasticities and average Student's t per expenditures items

	Income Elasticity	t-Student	Price Elasticity	t-Student
Food	0.3	5.10 ***	-0.17	-3.20**
Electricity	0.49	10.75***	-0.67	-12.50***
Gas (natural and biogas)	1.3	26.02***	-0.16	-3.19**
Other residential energy	0.8	1.8°	-0.62	-1.47
Construction and construction services	1.33	4.44 ***	-0.26	-2.40*
First-hand vehicles	1.95	11.88***	-1.39	-3.37***
Vehicle fuels and lubricants	0.77	5.80***	-0.27	-4.56***
Rail and air transport	1.78	5.80***	-0.35	-1.47
Road and water transport	1.69	4.13***	-1.19	-1.39
Leisure services	1.57	41.49***	-0.2	-2.38*
Other services	1.13	44.61***	-0.22	-7.59***
Other consumption/equipment goods	1.36	36.85***	-0.39	-5.03***
Housing rents	0.44	1.81°	-0.97	-1.94*
Second-hand vehicles	2.74	3.63***	-0.71	-1.67°

Significance:°10% = 1.6 ; * 5% = 1.96; ** 1% = 2.58; *** 0.1% = 3.29. Yellow: significant at 10%, orange, not significant

1.B.2 Standard Errors

We compute the standard errors of the elasticities with the delta method (Greene, 2003; Colonescu, 2016). The delta method is a method of approximating the standard deviations of a function of estimated coefficients. In this chapter, the equations giving the price and income elasticities of the expenditure items considered are used. Let $h(x)$ be the function of the estimated coefficients, then the variance of the function $h(x)$ is given by

$$V(h(x)) = th'(x)V(x)h'(x), \tag{1.52}$$

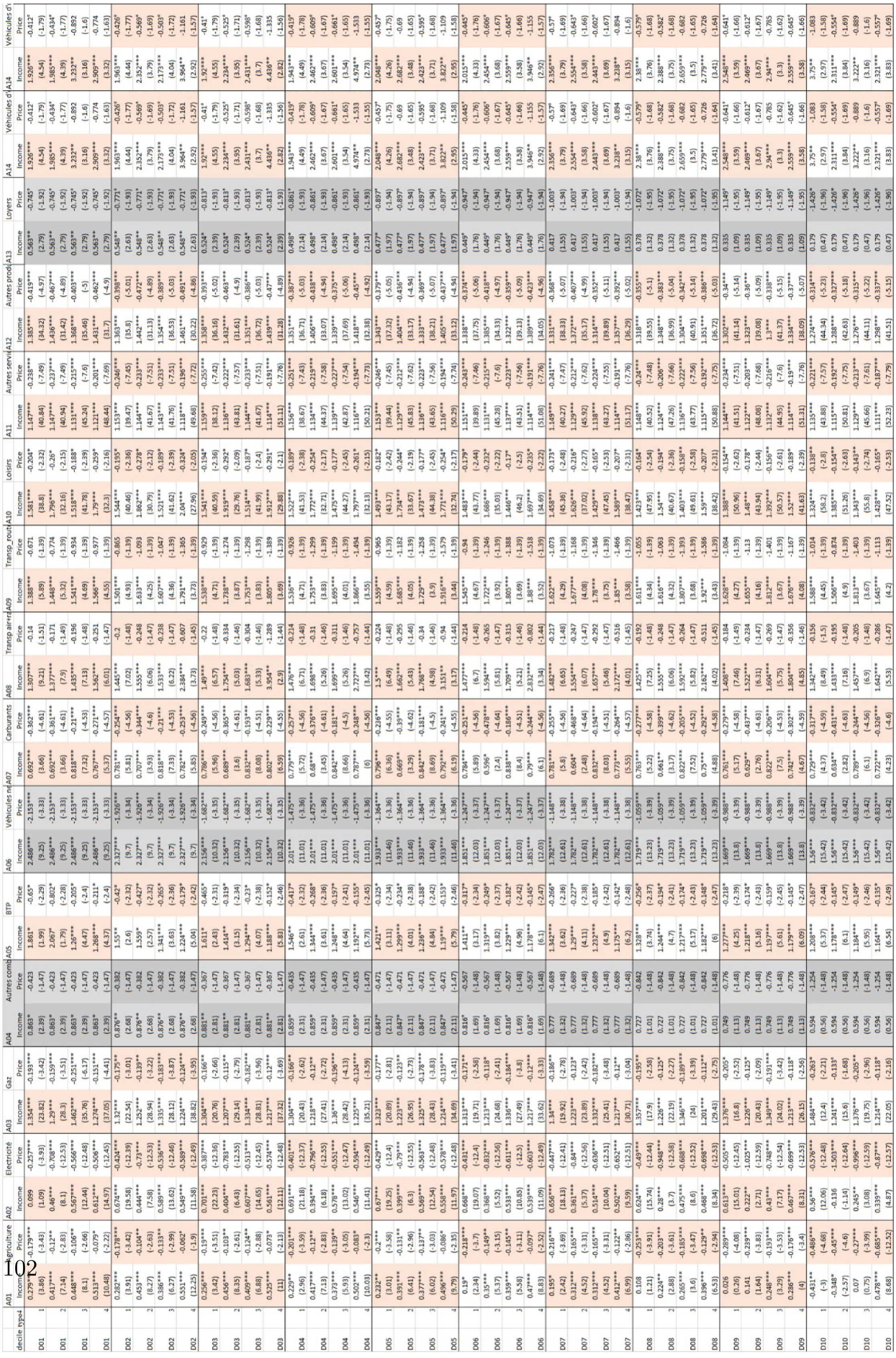
with $V(x)$ the variance-covariance matrix of the estimated coefficients x, $h'(x)$ the first derivative of the function $h(x)$ and t, the transposition operator of a vector.

All values and significance are indicated in Table 1.B.1. Aggregated values and t-Student values are available in Table 1.B.1. Disaggregated significance of price and income elasticities are available in Tables 1.B.3 and 1.B.2. Please refer to Table 1.C.4 for the nomenclature explicitation.

1.B.3 Quasi-balanced demand system

A system of demand should verify the following equations for each cell of households and the aggregated population:

Figure 1.B.1 – Long-term price and income elasticities of French households by decile and vulnerability type



Source: Authors calculations. Reading: households in decile 1, type I, have income and price elasticities of 0.28 and -0.18 for agricultural products; 0.46 and -0.70 for electricity; etc. We estimated the shaded elasticities without distinction of class (A04; A06; A13). Significance thresholds: * 5% = 1.96 ; ** 1% = 2.58 ; *** 0.1% = 3.29. In brackets we indicate the values of the Student's t-test.

Table 1.B.2 – Significance of income elasticities

Income decile	Vulnerability type	A01	A02	A03	A04	A05	A06	A07	A08	A09	A10	A11	A12	A13	A14
D1	I	***	***	***	*	*	***	***	***	***	***	***	***	**	***
D1	II	***	***	***	*	°	***	***	***	***	***	***	***	**	***
D1	III	***	***	***	*	***	***	***	***	***	***	***	***	**	**
D1	IV	***	***	***	*	***	***	***	***	***	***	***	***	**	***
D2	I	***	***	***	**	**	***	***	***	***	***	***	***	**	***
D2	II	***	***	***	**	*	***	***	***	***	***	***	***	**	***
D2	III	***	***	***	**	***	***	***	***	***	***	***	***	**	***
D2	IV	***	***	***	**	***	***	***	***	***	***	***	***	**	**
D3	I	***	***	***	**	*	***	***	***	***	***	***	***	*	***
D3	II	***	***	***	**	**	***	***	***	***	***	***	***	*	***
D3	III	***	***	***	**	***	***	***	***	***	***	***	***	*	***
D3	IV	***	***	***	**	***	***	***	**	***	***	***	***	*	**
D4	I	**	***	***	*	**	***	***	***	***	***	***	***	*	***
D4	II	***	***	***	*	***	***	***	***	***	***	***	***	*	***
D4	III	***	***	***	*	***	***	***	***	***	***	***	***	*	***
D4	IV	***	***	***	*	***	***	***	***	***	***	***	***	*	**
D5	I	**	***	***	*	**	***	***	***	***	***	***	***	*	***
D5	II	***	***	***	*	***	***	**	***	***	***	***	***	*	***
D5	III	***	***	***	*	***	***	***	***	***	***	***	***	*	***
D5	IV	***	***	***	*	***	***	***	**	***	***	***	***	*	**
D6	I	*	***	***	°	**	***	***	***	***	***	***	***	°	***
D6	II	***	***	***	°	***	***	*	***	***	***	***	***	°	***
D6	III	***	***	***	°	***	***	***	***	***	***	***	***	°	***
D6	IV	***	***	***	°	***	***	***	***	***	***	***	***	°	**
D7	I	*	***	***	0.2	***	***	***	***	***	***	***	***	0.2	***
D7	II	***	***	***	0.2	***	***	*	***	***	***	***	***	0.2	***
D7	III	***	***	***	0.2	***	***	***	***	***	***	***	***	0.2	***
D7	IV	***	***	***	0.2	***	***	***	***	***	***	***	***	0.2	**
D8	I	0.3	***	***	0.4	***	***	***	***	***	***	***	***	0.2	***
D8	II	**	***	***	0.4	***	***	**	***	***	***	***	***	0.2	***
D8	III	***	***	***	0.4	***	***	***	***	***	***	***	***	0.2	***
D8	IV	***	***	***	0.4	***	***	***	***	***	***	***	***	0.2	***
D9	I		**	***	0.3	***	***	***	***	***	***	***	***	0.3	***
D9	II	0.2	***	***	0.3	***	***	**	***	***	***	***	***	0.3	***
D9	III	**	***	***	0.3	***	***	***	***	***	***	***	***	0.3	***
D9	IV	***	***	***	0.3	***	***	***	***	***	***	***	***	0.3	***
D10	I	**	0.3	***		***	***	***	***	***	***	***	***		**
D10	II	*	**	***		***	***	**	***	***	***	***	***		***
D10	III	0.5	***	***		***	***	***	***	***	***	***	***		**
D10	IV	0.3	***	***		***	***	***	***	***	***	***	***		***

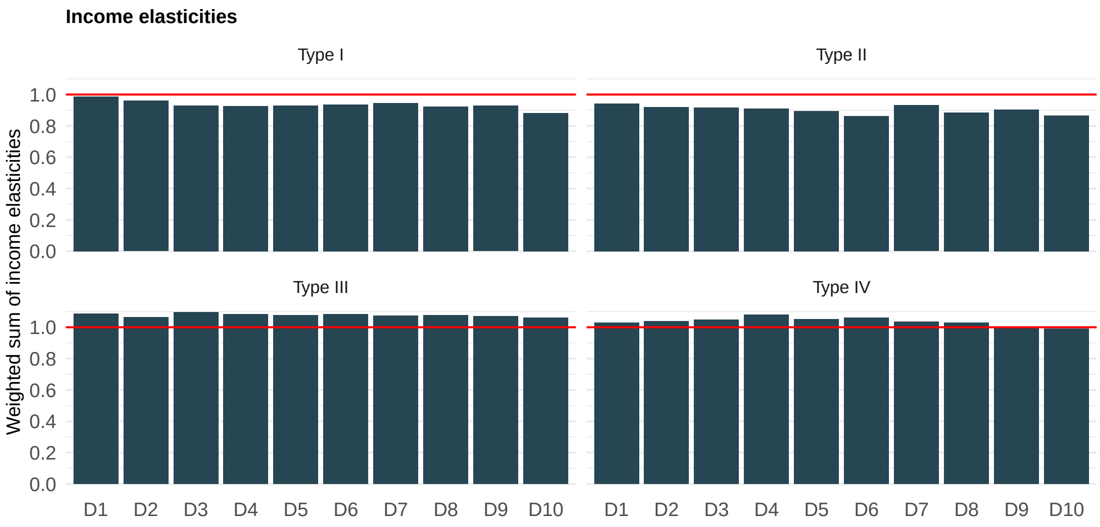
Significance: °10% = 1.6 ; * 5% = 1.96; ** 1% = 2.58; *** 0.1% = 3.29. Other low significance levels are indicated in the table.

Table 1.B.3 – Significance of price elasticities

Income decile	Vulnerability type	A01	A02	A03	A04	A05	A06	A07	A08	A09	A10	A11	A12	A13	A14
D1	I	***	***	***	0.2	*	***	***	0.2	0.2	*	***	***	°	°
D1	II	**	***	***	0.2	*	***	***	0.2	0.2	*	***	***	°	°
D1	III	**	***	***	0.2	*	***	***	0.2	0.2	*	***	***	°	0.2
D1	IV	*	***	***	0.2	*	***	***	0.2	0.2	*	***	***	°	0.2
D2	I	***	***	**	0.2	*	***	***	0.2	0.2	*	***	***	°	°
D2	II	**	***	**	0.2	*	***	***	0.2	0.2	*	***	***	°	°
D2	III	**	***	***	0.2	*	***	***	0.2	0.2	*	***	***	°	°
D2	IV	°	***	***	0.2	*	***	***	0.2	0.2	*	***	***	°	0.2
D3	I	***	***	**	0.2	*	***	***	0.2	0.2	*	***	***	°	°
D3	II	**	***	**	0.2	*	***	***	0.2	0.2	*	***	***	°	°
D3	III	**	***	***	0.2	*	***	***	0.2	0.2	*	***	***	°	°
D3	IV	*	***	***	0.2	*	***	***	0.2	0.2	*	***	***	°	0.2
D4	I	***	***	**	0.2	*	***	***	0.2	0.2	*	***	***	°	°
D4	II	**	***	**	0.2	*	***	***	0.2	0.2	*	***	***	°	°
D4	III	**	***	***	0.2	*	***	***	0.2	0.2	*	***	***	°	°
D4	IV	*	***	***	0.2	*	***	***	0.2	0.2	*	***	***	°	0.2
D5	I	***	***	**	0.2	*	***	***	0.2	0.2	*	***	***	°	°
D5	II	**	***	**	0.2	*	***	***	0.2	0.2	*	***	***	°	°
D5	III	**	***	***	0.2	*	***	***	0.2	0.2	*	***	***	°	°
D5	IV	*	***	***	0.2	*	***	***	0.2	0.2	*	***	***	°	0.2
D6	I	***	***	**	0.2	*	***	***	0.2	0.2	*	***	***	°	°
D6	II	**	***	*	0.2	*	***	***	0.2	0.2	*	***	***	°	°
D6	III	**	***	***	0.2	*	***	***	0.2	0.2	*	***	***	°	°
D6	IV	*	***	***	0.2	*	***	***	0.2	0.2	*	***	***	°	0.2
D7	I	***	***	**	0.2	*	***	***	0.2	0.2	*	***	***	°	°
D7	II	***	***	*	0.2	*	***	***	0.2	0.2	*	***	***	°	°
D7	III	***	***	***	0.2	*	***	***	0.2	0.2	*	***	***	°	°
D7	IV	**	***	**	0.2	*	***	***	0.2	0.2	*	***	***	°	0.2
D8	I	***	***	**	0.2	*	***	***	0.2	0.2	*	***	***	°	°
D8	II	***	***	*	0.2	*	***	***	0.2	0.2	*	***	***	°	°
D8	III	***	***	***	0.2	*	***	***	0.2	0.2	**	***	***	°	°
D8	IV	**	***	**	0.2	*	***	***	0.2	0.2	*	***	***	°	0.2
D9	I	***	***	*	0.2	*	***	***	0.2	0.2	**	***	***	°	°
D9	II	***	***	*	0.2	*	***	***	0.2	0.2	*	***	***	°	°
D9	III	***	***	***	0.2	*	***	***	0.2	0.2	**	***	***	°	0.2
D9	IV	***	***	*	0.2	*	***	***	0.2	0.2	*	***	***	°	°
D10	I							***	0.2	0.2	**	***	***	*	0.2
D10	II							***	0.2	0.2	**	***	***	*	°
D10	III							***	0.2	0.2	**	***	***	*	0.2
D10	IV							***	0.2	0.2	*	***	***	*	°

Significance: °10% = 1.6 ; * 5% = 1.96; ** 1% = 2.58; *** 0.1% = 3.29. Other low significance levels are indicated in the table.

Figure 1.B.2 – Weighted sum of income elasticities by budget share



Source: Authors calculations. Note: The value of the carbon tax is 158€/tCO_2 .

$$\begin{cases} 1 = \sum_i w_0^i \left(1 + \varepsilon_p^i \frac{\Delta p_i}{p_i^0}\right)\left(1 + \frac{\Delta p_i}{p_i^0}\right) \\ 1 = \sum_i w_0^i \varepsilon_r^i \end{cases} \tag{1.53}$$

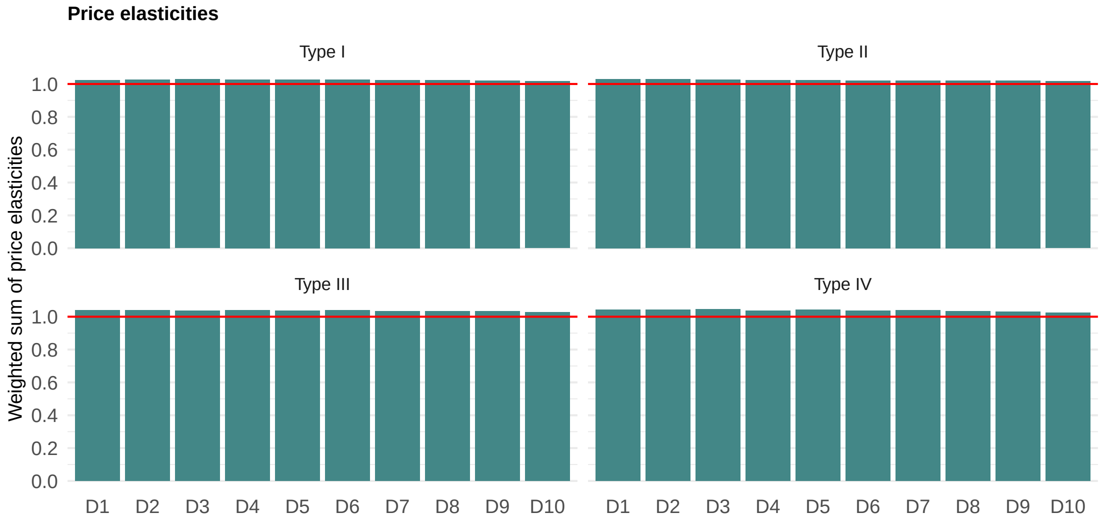
Using the 158€/tCO_2 carbon tax, the weighted sum of elasticities is equal to 0.9997697 for income elasticities and to 1.03 for price elasticities. For all 40 cells, the median value for the weighted sum of income elasticities is 0.990 and 1.03 for price elasticities (Figure 1.B.2 and 1.B.3). It is therefore reasonable to use these elasticities as a quasi-system and to close the budget in the microsimulation by reallocating surpluses or shortfalls to the budget using the income elasticities (see section 3.2).

1.C Robustness analysis

1.C.1 Uncertainty on elasticities

We assess the propagation of uncertainty from the estimated coefficients of the Engel curves using a Monte-Carlo simulation on all elasticities. Income and price elasticities are non-linear functions of estimated coefficients (see section 2.3). Therefore, we cannot compute covariance matrices between elasticities. We approximate uncertainty propagation with the assumption of full independence of all elasticities even if it obviously

Figure 1.B.3 – Weighted sum of price elasticities by budget share



Source: Authors calculations. Note: The value of the carbon tax is 158€/tCO_2 .

overestimates the dispersion of results. The outcome of Monte-Carlo is the emissions of each income decile following the introduction of carbon tax (price effect) and the lump-sum transfer (income effect) as modelled in section 4. We launch 26,000 runs of the model, each of the 1125 elasticities following a specific gaussian distribution (see figures 1.1 and 1.2 for the mean and appendix 1.B.2 to discuss the computation of standard errors). We plot the distribution of the aggregate level of emissions and the distribution of each income deciles emissions.

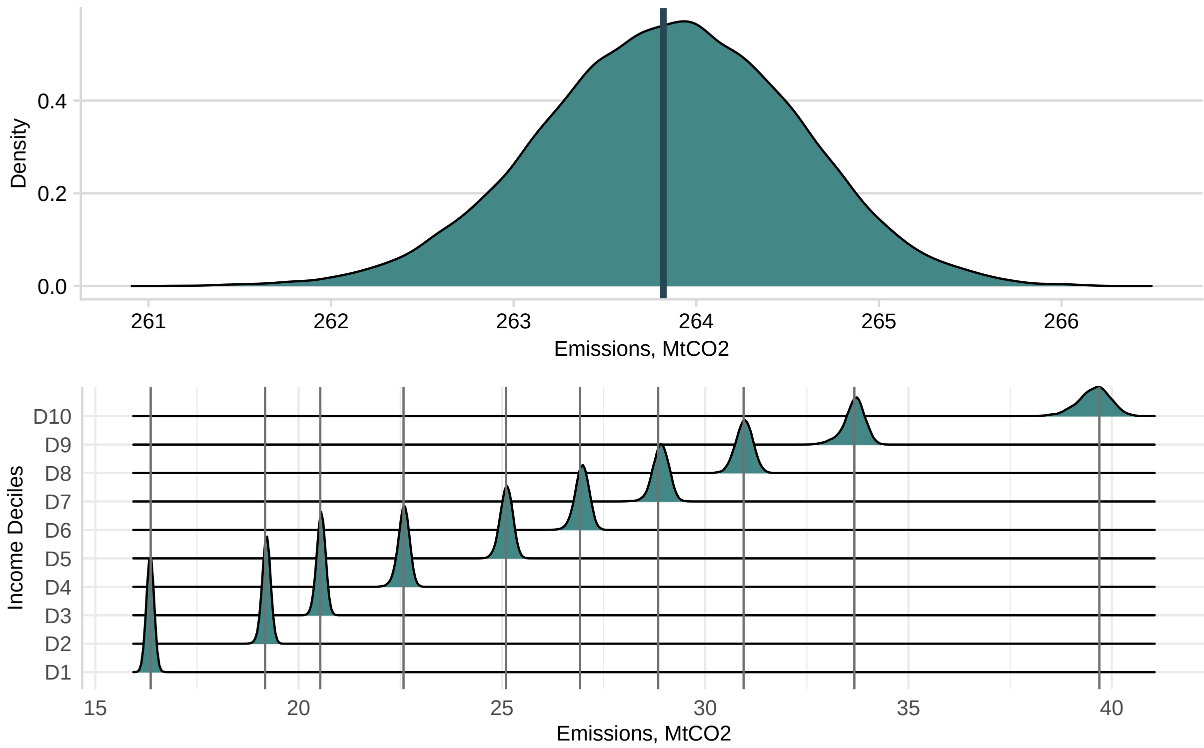
We show in Figure 1.C.4 that the distribution of uncertainty is almost gaussian for each income decile emissions distribution and aggregated emissions. The outcome obtained using mean expectations as per in section 3.3 is within the 99.9% interval of confidence. Uncertainty is obviously higher for richer households as their larger emissions are more sensitive to changes in elasticities.

1.C.2 Alternative carbon intensity for electricity

Carbon footprint The quantity of CO_2 emitted per euro spent is about 1662gCO_2 /€, which means about 200gCO_2 /MWh (using 119€/MWh, the average price of a MWh of electricity from table 2.9 in De Lauretis (2017)). The current carbon footprint of electricity production on the French national territory in 2022 is about 60gCO_2 /MWh.

The carbon intensity of electricity appears to be high (Table 1.C.4) when electricity is supposed to be decarbonised in France. We attempt to explain this figure and then test the robustness of our simulations if we adopt a lower figure.

Figure 1.C.4 – Distribution of final emissions of households, using Monte-Carlo simulations on price and income elasticities



Note: For each of the 26,000 simulations, we independently draw each of the elasticities in a Gaussian distribution. The vertical lines indicate the volume of emissions using the mean expectations. The value of the carbon tax is 158€/tCO_2 .

One reason is that part of the household energy bills in BDF are joint gas and electricity bills. Pottier (2022) following De Lauretis (2017) allocates the bills to electricity and natural gas using the same pattern as households using the same heating system and separable bills between gas and electricity. This correction is doubtlessly the best one can do but suffers from several biases. The first is that the main heating system is a weak variable as hot water and heating system can be different, most households who benefit from urban heating do not know it, etc. Second, the quality of heating systems can vary widely between an efficient global electric heater to multiple "toaster-like" small electric heaters. Some households in collective housing also benefit from shared heating systems where heating bills are included in the service charge (with other utilities).

Another reason is that the costs and emissions of investment in production have been included in the sector's emissions and therefore increase them.

Table 1.C.4 – Expenditures Nomenclature and carbon intensity of consumption

Code	Description	Carbon intensity (gCO_2 per euro spent)
A01	Food	185.2
A02	Electricity	1662.8
A03	Gas (natural and biogas)	1835.5
A04	Other residential energy	2024.8
A05	Construction and construction services	138.1
A06	First-hand vehicles	257.6
A07	Vehicle fuels and lubricants	2722.9
A08	Rail and air transport	773.0
A09	Road and water transport	773.0
A10	Leisure services	93.0
A11	Other services	164.4
A12	Other consumption/equipment goods	176.6
A13	Housing rents	121.9
A14	Second-hand vehicles	257.6

Note: Carbon intensities are from Pottier et al. (2020). Carbon intensities are expressed in gCO_2 par euro spent (constant € 2010), they include direct and indirect emissions. See Nadaud (2020) for detailed aggregation from the Classification of Individual Consumption by Purpose (COICOP).

Robustness test We have run robustness tests using a smaller carbon footprint of electricity. 60gCO_2 /MWh translates into 500gCO_2 /€ in 2010. Using this value, we estimate the carbon tax and recycling to reduce emissions by 5.5% (versus 5.9% in the main scenario), and without recycling the carbon tax revenues, the reduction would be of 9.8% (versus 10.9% in the main scenario). All of our conclusions and analysis stand.

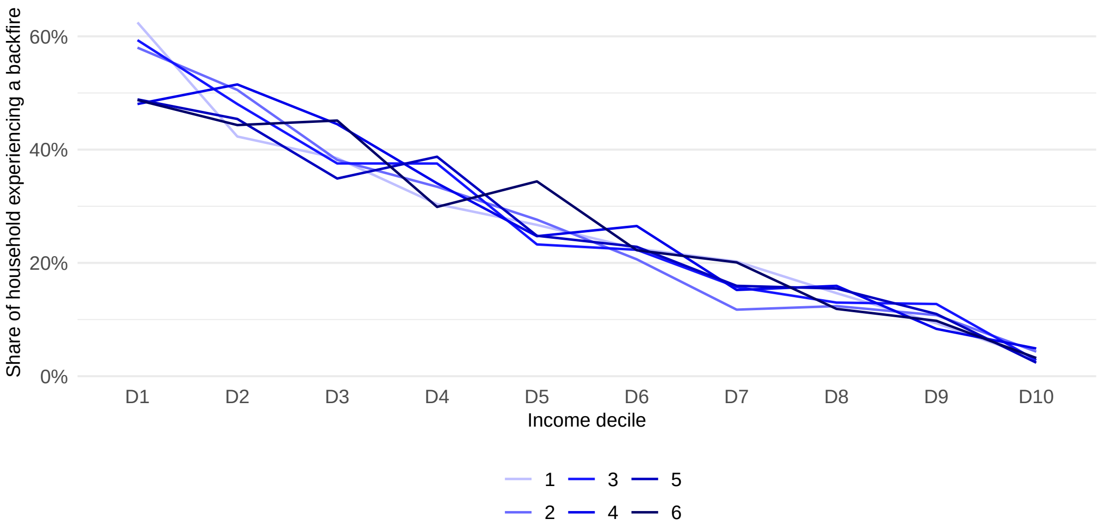
The reduction is somewhat smaller because the price elasticity of electricity is larger in absolute terms than other goods (natural gas or gasoline for instance) with lower income elasticities. The magnitude of the backfire effect (35% of households increase their emissions) is higher than in the previous exercise: the high price elasticity on electricity can no longer offset the income effects on other items.

The carbon tax is still regressive with respect to income on D1-D10, but only regressive on D7-D10 with respect to total consumption (compared to D5-D10 with the emission coefficients of (Pottier et al., 2020))

1.C.3 Wave influence on the backfire effect

It does not appear that the wave of the consumer expenditures influences the share of household increasing their emissions above the pre-tax level. The exception being the first income decile where the variation in the share of backfire households decrease with the wave.

Figure 1.C.5 – Share of household experiencing a backfire per wave of survey



CHAPTER 2

Is a fair energy transition possible? Evidence from the French Low-Carbon Strategy

Joint work with Frédéric Ghersi (CNRS-CIRED) and Franck Nadaud (CNRS-CIRED)

Toutes les familles heureuses se ressemblent. Chaque famille malheureuse, au contraire, l'est à sa façon.

Léon Tolstoï, *Anna Karénine*

Abstract

The distributional consequences of environmental policies are a major issue for the public acceptability of energy transitions, as the Yellow-vest demonstrations highlighted. Our objective is to assess the short and mid-term distributional impacts of policy packages on firms and households – rather than of single policy instruments — including carbon taxing, technology adoption subsidies and compensating lump-sum transfers. We offer insights on the fair transition promoted by the EU Fit-for-55 proposal with a case-study on two successive versions of the French low-carbon strategy. To that end, we develop an innovative numerical method that combines micro-simulation and macroeconomic modelling techniques. We explicitly model the heterogeneity of households' behaviour and the role of the distribution of energy-efficient durable technologies — electric vehicles, energy-efficient housing — among consumers. Focusing technology adoptions on the largest energy consumers to maximise emission reductions reduces the discrepancy of impacts between rural and urban households. However, it aggravates the regressivity of carbon taxation if households are not rebated their carbon tax payments. Recycling schemes favouring poorer households are powerful means to offset the regressivity of carbon taxation in the short term. In parallel, policies supporting electric vehicles and thermal renovation are effective in reducing households' tax payments at further horizons.

1 Introduction

According to the United Nations, "Climate Change is the defining issue of our time and we are at a defining moment" (UN website, December 2021). Without dramatic changes in trajectories, major threats to human activity are bound to concretise. In December 2019, the European Union consequently became one of the first major economies to announce net zero emissions of greenhouse gases by 2050. In July and December 2021, it released the 'Fit for 55' policy package aiming at this objective. The very ambition of the transformation calls for thorough assessments of both the efficiency of transition pathways — how are they going to influence aggregate economic activity and welfare? — and their equity consequences — how are their costs and benefits going to distribute across economic agents? This chapter contributes to the latter question by assessing the distributional consequences of France's 2015 and 2020 energy transition propositions up to 2035.

Assessing the distributional impacts of climate policies has been a topic of academic interest for several years (Baumol and Oates, 1988; Ekins et al., 2011; Fleurbaey et al., 2014; Lamb et al., 2020). It has become clear that the political acceptability of environmental reforms is closely linked to fairness, whether perceived or real (Maestre-Andrés et al., 2019; Büchs et al., 2011). The Yellow vest movement in France has demonstrated how the perception of carbon taxes as unfair (Douenne and Fabre, 2020) can sparkle severe popular unrest.

Recent literature draws mixed conclusions about the regressivity of carbon taxes and other environmental policies (Dorband et al., 2019; Ohlendorf et al., 2020; Wang et al., 2016).[1] In the case of France, Italy and (to a lesser extent) Germany, a carbon tax on direct emissions would be slightly regressive relative to expenditures, but not in the case of other countries (Feindt et al., 2021; Symons et al., 2002). Berry (2019) and Douenne (2020) show that the carbon component of excise taxes on fossil fuel consumptions in France is regressive on all income deciles when measured against income. Känzig (2021) concludes from UK data and EU ETS shocks that carbon pricing is both efficient at cutting emissions and highly regressive, whether measured against income or against expenditures. A carbon tax on the full carbon footprint of households tends to be neutral relative to total consumption for European countries individually but regressive at the aggregate European level (Feindt et al., 2021). Indeed, the total carbon footprint of households tends to be proportional to expenditures, but the contribution of energy and individual transport consumptions to the carbon footprint decreases with income in developed countries (Isaksen and Narbel, 2017; Pottier et al., 2020).

Despite their contrasted findings on the partial or total regressivity of environmental policies, the above studies and several others (Carattini et al., 2019; Combet et al., 2009; Ekins and Dresner, 2004; Fremstad and Paul, 2019; Metcalf, 2019; Metcalf et al., 2010) conclude that recycling carbon tax revenues toward households can counter the

[1] Following the literature, we define a carbon tax as regressive when the ratio of carbon tax payments to income or expenditures is larger for poorer households than for richer ones. See section 4.2 for more discussion on the issue of measurement against income or expenditures.

regressivity of the carbon tax and can therefore increase social acceptability. Moreover, recycling can be complemented with subsidies (Baranzini et al., 2017), whose non-coercive 'pull' nature has higher public support (Drews and van den Bergh, 2016). In fact, most national low-carbon strategies consider the simultaneous implementation of several tools — taxes, subsidies, norms, regulations, etc. — whose distributional effects may amplify or offset each other (Fullerton, 2011; Vona, 2021). However, the distributive effects of such policy packages are little researched so far (Lamb et al., 2020). To the best of our knowledge, Bourgeois et al. (2021) and Giraudet et al. (2021) provide the only analyses of the cross-impacts of a carbon tax, support measures for energy efficiency technology and carbon tax recycling in a static partial-equilibrium framework.

By comparison, the contribution of our work lies in the comprehensive analysis of the distributive impacts, both vertical (across income classes) and horizontal (following other non-income dimensions), of low-carbon policy packages in a dynamic, general-equilibrium framework. To do so, we implement an original 'macro-micro methodology, whose microsimulation component improves on current tools of distributive assessment of transition packages by (1) resting on long-term elasticities differentiated for 40 classes of households and 14 goods and services, to forecast household consumption patterns following price and income evolutions (2) modelling explicitly technical change brought by the adoption of electric vehicles and the massive thermal renovation of dwellings, which escape historical trends, and (3) providing dynamic outlooks at 2025, 2030 and 2035 temporal horizons.

Our case study bears on two successive versions of the French Low-Carbon Strategy (SNBC in its French acronym), whose level of ambition has been raised from the 'Factor 4' objective of a cut of 75% of 1990 emissions (SNBC 1, 2015) to the carbon neutrality of 'net zero emissions' (SNBC 2, 2020) by 2050. The two packages are meant as part of a coordinated global effort to limit global warming to 2°C and 1.5°C, respectively. They include carbon tax trajectories, recycling options, energy mix prescriptions, housing renovation subsidies, bonus-malus schemes for conventional and electric vehicles and various measures additionally targeting emissions in all activity sectors. Our method of analysis rests on the iterative linkage between micro-simulation on a 10,000-household database and macroeconomic modelling of the aggregate economy. Our macroeconomic modelling calibrates on input-output tables from the official macroeconomic evaluation of the two policy packages.

The rest of our chapter organises as follows. In Section 2, we describe the three main drivers of the distributional impacts of carbon-control policies. In Section 3, we present the original numerical tool that we built to address the blueprint emerging from Section 2. In Section 4, we present modelling results, successively considering a brief overview of the macroscopic impacts of disaggregating households when assessing low-carbon strategies (section 4.1); the distributional impacts of low-carbon transition without carbon payments recycling (section 4.2); a focus on the role of housing energy efficiency and electric vehicles subsidies (section 4.3); and the complementarity of subsidies and lump-sum recycling of carbon payments (section 4.4). We summarise our results in Section 5.

2 Drivers of the distributional impacts of climate policies

We focus this section on three main determinants of the distributive effects of climate policies, which frame our methodological choices and differentiate our analysis from the literature: the heterogeneity of household behaviour, the macro-economic feedback effects and the penetration of energy-efficient technologies in households. We refer to the literature for more detail on additional drivers (Ghersi, 2014; Ohlendorf et al., 2020; Stiglitz, 2019; Wang et al., 2016). Due to lack of data, we do not take into account the heterogeneous effects of environmental policies on total employment (Ekins and Speck, 2011; Fullerton and Heutel, 2007) and employment of more or less skilled workers by sector (Marin and Vona, 2019; Vona, 2021). We also focus our analysis on carbon emissions and do not consider health and environmental quality incidences and benefits that can arise from the considered policies (Drupp et al., 2021).

2.1 Heterogeneity of the adaptive behaviour of households

Lower income classes have more carbon-intensive consumptions and dedicate larger income shares to energy expenses, which makes carbon taxes regressive across income classes (Cronin et al., 2019; Flues and Thomas, 2015; Pizer and Sexton, 2019). However, many factors largely independent from income shape the energy consumptions of households, hence their sensitivity to carbon-control policies, from housing characteristics (insulation, size, individual or collective) to geography (density, climate of residence area) to socio-economic variables (household composition, occupational status of household members) (Büchs and Schnepf, 2013; Douenne, 2020; Poterba, 1991). Typically, carbon taxes weigh more on the budgets of rural households living in poorly insulated individual houses and heavily dependent on personal car use irrespective of their wealth (Büchs et al., 2011). 'Horizontal' inequalities among households of the same income class may, in fact, be as large as 'vertical' inequalities across income-class averages (Cronin et al., 2019; Ekins and Dresner, 2004).

Both vertical and horizontal inequalities affect households' behavioural responses to price signals; they vary according to their adaptation or deprivation capacities. Douenne (2020), for instance, estimates the price and income elasticities of 3 goods (transport fuels, residential energy consumptions and non-energy goods) for 50 categories of French households defined by two criteria: income (10) and size of urban unit of residence (5). The first chapter of this dissertation refines the method by calculating the long-term and income elasticities of 14 goods and services, including 4 energy goods, proving that low-income households have higher fuel price elasticities than richer ones, but that rural households tend to be more fuel dependent and have lower price elasticities. Accounting for households' behaviour on larger numbers of goods allows pinpointing direct and indirect carbon tax payments and 'rebound effects' from energy savings or compensation payments. More aggregated approaches, e.g. that of Douenne (2020), or partial equilibrium approaches, only present fragmented views of the impacts of carbon taxes. Typically, thermal renovations reduce heating consumption and thus free up income, which households can partially use to increase energy consumption again.

2.2 Policy signals and their propagations in the economic system

Carbon-control policies affect households through three distinct channels. The first is the direct effect of policies on the prices and availability of energy and energy-consuming equipment — "use-side" impacts.[2] The second channel is the set of indirect effects of price and non-price measures on the production costs of firms. Cost shifts loop from firm to firm via the input-output structure of inter-sectoral exchanges. They end up modifying the relative prices of consumer goods and services. The third channel of impact is the set of feedbacks from all markets incurring price shifts. The relative price variations from the first and second channels retroact on the consumers' and the producers' consumption and input choices. Hence, on factor demands and payments, and finally on households' income. These "resource-side" impacts can offset the carbon tax regressivity as social benefits rise and carbon-intensive sectors — which often are capital-intensive as well — shrink (Goulder et al., 2019; Rausch et al., 2011).

Despite their sequential presentation, the three channels occur simultaneously. This interdependency requires considering them in one unified computational framework where their interactions play up to some equilibrium. Cockburn et al. (2014) review modelling efforts to integrate the heterogeneity of microeconomic models into macroeconomic frameworks. We stress here the most important references for our model. Chen and Ravallion (2004) were among the firsts to develop one-way linkage from macroeconomic modelling to microsimulation. Rausch et al. (2011) refined the method by directly integrating 15,000 households into their macroeconomic model to compute feedback effects. Their fully integrated approach is the theoretically soundest (Bourguignon et al., 2008) but requires simplifying households' reaction functions to ensure consistency with macroeconomic modelling (Bourguignon and Savard, 2008). A simpler approach consists of an iterative exchange of data between macroeconomic modelling and micro-simulation. Buddelmeyer et al. (2012) and Vandyck and Van Regemorter (2014) perform such 'soft-linking' by adjusting the representativeness weights of survey households (see section 3.4), but do not consider retroactions from microsimulation to macroeconomic modelling.

2.3 Penetration of electric vehicles and renovation technologies

Estimating the adaptive behaviour of households conventionally rests on econometric analysis linking past consumer choices to past price and income variations. However,

[2] In the case of the second SNBC (SNBC 2), this channel covers the impact of the carbon tax on the prices of natural gas and petroleum products; of the bonus/malus provision on the prices of private vehicles; and of subsidies on the investment costs of housing insulation, space-heating and water-heating equipment.

such statistics only describe the trends of evolution of households' preferences and cannot convey any information on the consequences of disruptive technological changes. Ambitious climate policies as the French SNBC envision two such changes: the electrification of personal cars and the dramatic increase of the thermal efficiency of buildings.

The electric vehicle technology is only gradually reaching maturity, as ranges catch up on those of conventional alternatives while prices decrease. Consequently, the income and price elasticities of vehicle fuels and electricity consumptions of past decades cannot be related by the direct substitution possibility that electric mobility only begins to embody. The case of thermal efficiency gains, which originate in the oil shocks of the 1970s, is rather of quantitative nature: the obligation of renovation at any change of occupancy, the ambition of renovations and the commitment to renovate all public-owned buildings (17% of the current housing stock in France) at unprecedented rate mark a change of regime. Accounting for these two technical disruptions requires extending numerical methods beyond econometric analysis.

Both technologies have significant distributional consequences. For example, the least energy-efficient dwellings are inhabited by poorer-than-average households, who are therefore more affected by renovation policies. Conversely, the largest consumers of vehicle fuels are rural and wealthy households, who will therefore benefit more from electric vehicle subsidies.

3 Computational method

The previous section provides the blueprint of our methodology. To consider the heterogeneity of households, like a growing number of studies, we rely on microsimulation, which we operate on a database of more than 10,000 households. To capture feedback effects from the economic system, we additionally mobilise macroeconomic modelling, which we combine with microsimulation through the iterative exchange of linking variables rather than one-way coupling only. Lastly, our microsimulation originally extends to the explicit modelling of electric vehicle adoption and thermal renovation consequences.

3.1 Data and scenario description

We use microeconomic data from the latest French consumer expenditure survey, Budget des Familles (BDF), performed in 2010-2011 by the French statistical agency INSEE. The database provides the exhaustive breakdown of income sources and expenditures of more than 15,000 French households characterised by hundreds of demographic, geographic and socio-economic series. Out of this set, we focus our analyses on the slightly more than 10,000 households of metropolitan France. We use several series of variables matched to BDF from other databases to expand BDF to physical energy consumptions and the energy performance diagnosis (EPD) of dwellings.[3]

[3]See De Lauretis (2017) and Douenne (2017) for more detail.

Our macroeconomic data is not the usual Input-Output table for some statistical year. Rather, we calibrate on outlooks from the official macro-modelling of low carbon strategies by the French Agency for Ecological Transition (ADEME) using the ThreeME model (Callonnec et al., 2016, 2013). These 'SNBC input-output tables' are specific to each scenario and time horizon. Our macroeconomic model calibrates on them and performs comparative statics analysis while embarking aggregate household behaviour explicitly addressing dynamic adjustments from calibration year (the year of the BDF household survey) to time horizon.

We study two carbon control scenarios at three forecast horizons 2025, 2030 and 2035. The 'Factor 4' (F4) scenario, which corresponds to the 2015 version of the SNBC, aims at bringing net French emissions at 25% their 1990 level in 2050. The 'Net Zero Emissions' (NZE) scenario, which corresponds to the updated 2020 SNBC[4], targets 2050 carbon-neutrality. We derive three extra scenarios from NZE, where we contain respectively the carbon tax, thermal renovation subsidies and vehicle bonuses-maluses to their levels in the F4 scenario.[5]

In 2010, the starting point of our analysis for both scenarios, no carbon price for either firms or households was in place in France. The distributional impacts that we analyse are therefore entirely related to the measures put in place between 2010 and 2035 (Table 2.1). However, it should be noted that specific taxes on fuels have been in place for almost a century in France. The evolution of fuel taxes excluding carbon pricing is common to both the F4 and NZE scenarios. The carbon tax comes on top of these excise fuel taxes and exacerbates the distributive impacts of heterogeneous fuel consumptions.

The SNBC assumes recycling of their carbon tax payments to firms and households but does not pinpoint any distribution scheme. We first explore distributional consequences in the absence of recycling (to both firms and households), then test several rebating schemes to households under the shared assumption that firms' payments are rebated as output tax credits.

To summarise, for all scenarios and at each time horizon we use official SNBC data from ADEME regarding: 24-good input-output tables at horizon; yearly level of carbon tax up to horizon; yearly volume (m^2) of housing in each energy performance diagnosis (EPD) class from A to G, up to horizon; yearly volumes of thermal renovation for each EPD transition with renovation cost per square meter and mean energy gain, up to horizon; yearly composition of vehicle fleet per fuel (conventional versus electric) up to horizon; fuel-efficiency gains of conventional vehicles, up to horizon; yearly malus-bonus per type of vehicle purchase.

[4]French Ministry for Ecological and Inclusive Transition (MTES) description of the SNBC https://www.ecologie.gouv.fr/sites/default/files/2020-03-25_MTES_SNBC2.pdf

[5]See Appendix 2.B for the full descriptive of our scenarios.

Table 2.1 – Main elements of Factor 4 and Net Zero Emissions policy packages

	Factor Four (F4)	**Net Zero Emissions (NZE)**
Carbon tax in 2035 (€ 2019)	€26.8/tCO_2	€246/tCO_2
Housing Renovation		
Thermal renovation (2010-2035)	500 million m^2	1 billion m^2
Renovations per year	220,000 dwellings	700,000 dwellings
Subsidies to renovation	—	11.5% of cost
Subsidies (2010-2035, € 2019)	€7 billion	€15 billion
New Buildings		
New efficient building	20.0 million m^2	19.5 million m^2
		Energy self-sufficiency from 2020 on
Electric Vehicles (EV)		
Share of car sales in 2035	24%	49%
2035 Bonus (€ 2019)	€0/EV	€4400/EV

Source: French Agency for Ecological Transition (ADEME), and Ministry for Ecological and Inclusive Transition (MTES). See appendix 2.B for details.

3.2 The IMACLIM-3ME model

Our macroeconomic model is an adaptation of the static version of the IMACLIM[6] model developed at CIRED since the 1990s (Ghersi, 2015), which is specified to approach the behaviour of the ThreeME macroeconomic model used by ADEME to produce official SNBC estimations up to 2050 (Callonnec et al., 2016, 2013). The specifications retained after ThreeME concern macroeconomic assumptions, microeconomic behaviour, and a set of accounting rules on how the secondary distribution of income affects households' gross disposable income. We only detail these adjustments here and refer to (Ghersi, 2020) for exhaustive algebraic equations. We implement macroeconomic analysis in a 'comparative static' framework by operating IMACLIM-3ME independently at our three forecast horizons and for each scenario explored. Our numerical procedure gradually distorts the initial SNBC input-output tables to reflect the iterated response of our micro-simulation of households' behaviour.

Regarding macroeconomics, IMACLIM-3ME is of demand-driven neo-Keynesian inspiration. It endogenises the stock of capital and indexes its rental price on the producer price of investment goods, thereby implicitly assuming constant interest rates. It also models unemployment equilibrium through a 'wage curve' (Blanchflower and Oswald, 2005). Closure is on imported savings through adjustment of the real effective exchange rate under the constraint of investment demand proportional to the capital demand of sectors, and domestic savings proceeding from households' behaviour (see below) and endogenous public deficit. The latter deficit results from constant taxes

[6] See http://www.centre-cired.fr/en/imaclim-network-en/.

and excise duties applying to endogenous expenses, versus horizon-specific but scenario-independent real public expenditures.[7]

Concerning microeconomics, IMACLIM-3ME only represents the substitutability of capital and labour in production, that of imports and domestic products in supplies, and the implicit trade-off between French and foreign productions on international markets. All specifications reflect those of the Three-ME model of ADEME at the source of official SNBC outlooks, and replicate their elasticities of substitution.

3.3 Micro-simulation in the Budget de Famille household survey

We perform survey-based micro-simulation to aggregate households' behaviour with respect to relative price and income sources forecasts from the macroeconomic model. To this end, we developed the MATISSE model — Microsimulation Assessment within the low-carbon Transition of Inequalities and Sustainable Systems of Energy. MATISSE develops three steps of microsimulation and two steps of linkage to IMACLIM-3ME (Figure 2.1).

Step 1 consists in projecting the disposable incomes of BDF households to explored horizons (2025, 2030 or 2035). Macroeconomic analysis by IMACLIM-3ME — initially calibrated on official SNBC outlooks by ADEME — allows computing the increases, from 2010 on, of eight components of aggregate disposable income: domestic wages and benefits from self-employed activity, capital income, unemployment benefits, other social benefits including pensions, repatriated wages, international remittances, and on the side of expenses income taxes and other direct taxes.[8] We adjust homothetically the corresponding disposable income items of all households of our microeconomic database. The total disposable income of each household therefore increases depending on its initial structure.

Step 2 of the micro-simulation consists in households adapting their consumption choices to their projected disposable incomes and the macroeconomic evolution of the relative prices of 14 consumption goods and services: food, electricity, gas (natural and biogas), other residential energy, construction and construction services, first-hand vehicles, vehicle fuels and lubricants, rail and air transport, road and water transport, leisure services, other services, other consumption/equipment goods, housing rents, second-hand vehicles.[9] We use disaggregated long-term price and income elasticities

[7]The assumption of constant public expenditures at any given horizon reflects their indexation on (exogenous) potential growth in official SNBC outlooks.

[8]Due to well-known issues with matching data from consumer surveys and national accounts (André et al., 2016; Rausch et al., 2011), the information on income-source variations passing from macroeconomic modelling to microsimulation households is in the form of relative evolutions rather than absolute numbers. The downward link from macroeconomic modelling to microsimulation is thus performed with 8 increase factors for income sources, 14 increase factors for prices and 2 increase factors for tax rates.

[9]Price evolutions are computed for the 24 goods and services of IMACLIM-3ME then mapped to the 14 goods and services of the microsimulation. The two nomenclatures are compatible enough for

estimated by the first chapter of this dissertations on 40 classes of households. It is study is the most comprehensive and detailed on French consumers, building on 7 consecutive surveys from 1979 to 2010. The 40 classes correspond to the crossing of ten income deciles[10] and four categories of economic vulnerability grouping households with statistically similar pre-committed expenses (see (Nadaud, 2021)). The 40 classes of behaviour and the individualisation of income growth allow strong differentiation of households' consumption dynamics.

For each household, the update of good i expenditures from E_i^0 (2010) to E_i^1 (projection horizon) is summarised by the following equation (Equation 1), with $e_{E_iP_i}$ the elasticity of expenses to price Pi; e_{E_iX} the elasticity of consumption to income X; and P^* the Stone price index computed for each household[11] to deflate current prices, as price elasticities are calibrated on 2010 constant prices.

$$E_i^1 = E_i^0 \times (1 + e_{E_iP_i}) \cdot \left(\frac{P_i^1 - P_i^0}{P_i^0} \cdot \frac{1}{P^*} - 1 \right) \times (1 + e_{E_iX}) \cdot \frac{X^1 - X^0}{X^0} \cdot \frac{P_i^1 - P_i^0}{P_i^0} \quad (2.1)$$

The price and income elasticities calculated with such Engel curves warrant close-to constant savings rates. However, to avoid double counting of rebound effects on residential consumptions following thermal renovations, we introduce slight variations of the saving rate (see below).

Step 3 of our microsimulation is the original methodological contribution of representing explicitly the gradual penetration of disruptive technical progress, namely the massive thermal renovation of dwellings and electrification of personal vehicles. We model these penetrations in the database as the distribution of volumes of energy-efficient investments over subsets of households summing up to the aggregated SNBC target for the particular technology adoption. We modify the budget of each household in the subsets in response to these investments in new equipment: reduction in energy/fuel consumption, investment in new vehicle/renovation, interest payments on loans backing such investment, electricity expenses of electric vehicles and allocation of induced savings. We distinguish between investments made at projection horizons, whose effects are directly visible in projected budgets, and investments made between 2010 and projected horizons, of which only the induced perennial savings and expenses are visible in budgets at the horizons.[12] We also consider trends of efficiency gains of conventional

the mapping to be straightforward. The latter one results from a compromise between econometric relevance and explicit coverage of the main patterns of energy-intensive lifestyles. Nadaud (2021a) provides its correspondence with level 5 of the Classification of individual consumption by purpose (COICOP) nomenclature.

[10]By income decile we mean, here and hereafter, living-standard decile with living standard measured as income per consumption unit. The number of consumption units per household is 1 for the person of reference + 0.5 per individual 14 and above + 0.3 per individual below 14.

[11]The Stone Price index P^* of each cell is $ln(P^*) = \sum_{i=1}^{14} w_i \log(P_i)$ with w_i the budget share of item i in the cell and P_i the price index of item i (Green and Alston, 1990). Microsimulation means that the structure of expenditures of each household is likely to evolve. We iterate microsimulation to ensure full consistency of equation (2.1) and the resulting Stone price index.

[12]See Appendix 2.E for detail.

vehicles between 2010 and the horizon, as well as a homogeneous decrease of vehicle fuel consumptions from increased working from home.

Importantly, the subsets of households shifting to electric vehicles and moving from lower to higher EPD classes (the latter being specified for each possible class move) must be defined annually from 2010 to projected horizons. There are multiple possible criteria to do so, each of them with implementation issues. Typically, the economically efficient option of ordering technology shifts by net current value is hard to relate to plausible implementation policies.[13] We rather chose to frame the overall energy efficiency of the SNBC by exploring three variants of selection based on households' absolute energy consumptions. The 'maximum energy savings' variant selects each year, and for each technology shift, those households with the highest total energy consumptions. The 'median' and 'minimum' variants rather select households with median and lowest energy consumptions. Modelling such variants allows assessing the sensitivity of results to the allocation of technology incentives, and the extent to which energy savings computed on national averages hold when micro-simulated.

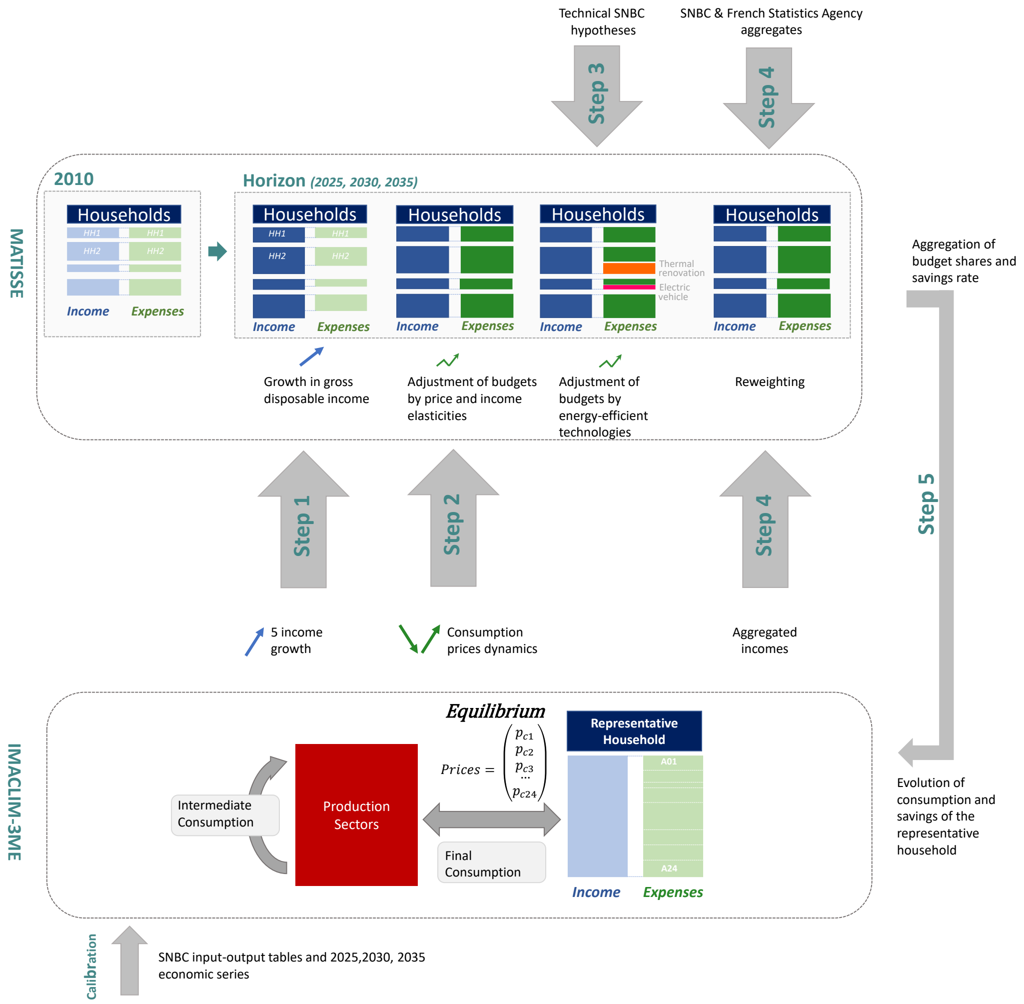
3.4 'Macro-micro' linkage of IMACLIM-3ME and MATISSE

Step 4 of our methodology (see Figure 2.1) is the adjustment of the representativeness weights of households of the microeconomic database, or 'reweighting', to ensure consistency with macroscopic variables beyond those linking to IMACLIM-3ME. Challenges and current trends in macro-micro modelling are described in Bourguignon and Savard (2008) and Cockburn et al. (2014). We follow the method introduced by Deville and Särndal (1992) and recently applied by Agénor et al. (2004), Buddelmeyer et al. (2012), Vandyck and Van Regemorter (2014) or De Lauretis (2017). We reweight under the maintained constraints of reproducing aggregate IMACLIM-3ME evolutions of total labour income, unemployment benefits, other social benefits (including pensions), capital income, the aggregate income tax, aggregate other direct tax. We expand to additional constraints concerning (1) demographic evolutions (total population, gender and age groups, active population) projected by INSEE as well as unemployment shifts computed by IMACLIM-3ME.[14] (2) Several sets of national totals maintained at survey values (shares of households' composition types, shares of collective versus individual housing, survey collect waves, distribution of households across regions and sizes of urban units). And (3) technology penetration (total housing surface by EPD class, the private vehicle fleet and the share of electric vehicles therein, the sales of thermal and electric vehicles). Among the infinite number of fitting weight adjustments, we choose the

[13] The costs of technical shifts to more efficient dwellings and electric vehicles are inputs from the official SNBC, which we apply to each selected household in proportion to housing surface and vehicle investment costs. There is therefore no a priori on the negative or positive sign of the net present value of forced shifts.

[14] Hérault (2010) checks the robustness of the reweighting approach compared to a behavioural model for employment and proves it to be a good approximation for distributional impacts.

Figure 2.1 – Computational method



adjustment that minimises quadratic deviation from the original set of weights (Agénor et al., 2004).

Step 5 is the aggregation of microsimulation results, feedback to IMACLIM-3ME and simulation update. The 'upward' link from MATISSE to IMACLIM-3ME is embodied in four increase factors (2010 to projection horizon) of absolute energy consumptions (oil and oil products, natural gas, coal and electricity), the remaining aggregated macroeconomic consumption shares and the aggregate saving rate.[15]

We iterate this 5-step procedure using the updated income and relative-price variations of Step 5 as a new starting point of Step 1. We stop the iteration when Step-5 information has converged below a 10-5 tolerance threshold, i.e. has not deviated by more than 0.001% from previous iteration. Convergence warrants consistency of the microsimulation and macroeconomic modelling of our exploration.

4 Modelling results

We start the review of our converged macro-micro modelling results by the benchmark policy case of no recycling of either the F4 or NZE carbon tax payments (sections 4.1, 4.2 and 4.3 with the exceptions of Tables 2.2 and 2.3). We first investigate the macroscopic effects of microsimulation results and hypotheses (section 4.1), then compare the distributional impacts of F4 and NZE (section 4.2) and the particular role of electric vehicle and thermal renovation support on inequality and carbon tax payment dynamics (section 4.3). We then extend the exploration to rebating options of the carbon tax payments (section 4.4).

4.1 Which households renovate and purchase electric vehicles strongly influences carbon emissions reductions

NZE additional investments into low-carbon options have a multiplier effect on activity that more than compensates the increased costs of energy services due to higher carbon prices. Indeed, NZE scores better than F4 in terms of GDP, unemployment rates and households' consumption at all projection horizons including 2035 (Table 2.2). This directly reflects the demand-driven structure of IMACLIM-3ME (see Section 3.2).[16] The three variants of distribution among households of electric vehicle and dwelling renovations impact macroeconomic results through feedback effects: induced energy savings are only partially offset by rebounds of consumption and households reallocate the net benefit between non-energy spending and savings (see section 3.3). Increased

[15] The R code of MATISSE is fully open source, available at https://github.com/eravigne/matisse.

[16] Macroeconomic studies in neoclassical frameworks condition such 'double dividend' (increased welfare or economic activity alongside decreased emissions) to the recycling of carbon tax proceeds into the reduction of pre-existing distortive taxations (Ekins et al., 2012; Goulder et al., 1999; Parry, 1995).

Table 2.2 – Evolution of macroeconomic indicators from 2010 to 2035

F4 Scenario	SNBC evaluation	Maximum energy savings	Median energy savings	Minimum energy savings
Real GDP	+45.2%	+43.6%	+43.6%	+43.2%
Unemployment rate	+0.9 pts	+1.7 pts	+1.7 pts	+2.0 pts
Trade Balance / GDP	-1.6 pts	-1.4 pts	-1.4 pts	-1.4 pts
Real Disposable Income	+42.7%	+41.5%	+41.4%	+41.0%
Saving Rate	id.	+1.4 pts	+1.3 pts	+1.7 pts
Real Consumption	+43.8%	+40.6%	+40.6%	+39.6%
NZE Scenario	SNBC evaluation	Maximum energy savings	Median energy savings	Minimum energy savings
Real GDP	+49.9%	+47.4%	+47.1%	+47.1%
Unemployment rate	-0.9 pts	+0.3 pts	+0.6 pts	+0.7 pts
Trade Balance / GDP	-1.7 pts	-1.0 pts	-0.8 pts	-0.8 pts
Real Disposable Income	+48.3%	+46.4%	+46.1%	+46.1%
Saving Rate	id.	+2.9 pts	+3.4 pts	+3.5 pts
Real Consumption	+51.2%	+44.9%	+43.8%	+43.7%

Note: Real changes are current-price changes corrected by specific deflators. Columns correspond to the official SNBC evaluation by the ThreeME model of ADEME (column 2) and the variants focusing electric vehicle and efficient dwelling adoptions on largest, median and smallest energy consumers (columns 3 to 5). Carbon tax payments of households are rebated in proportion of income per consumption unit (see footnote 10).

household savings reduce the national debt and improve the trade balance at the cost of a slight slowdown of activity.

The growth of real disposable income aggregates that of the different income sources of households (Table 2.3), whose contrasted evolutions impact income inequality. The real income gap from F4 to NZE is driven by rising capital income, at the benefit of capital owners i.e. the richer households.[17] This inequality trend is aggravated by the slight drop of social benefits, which represent 53% of income of the lower three deciles (D1-D3) against 24% for the higher three (D8-D10). The three variants of energy savings distribution marginally modify macroeconomic conditions, leading to differentiated income growth (Table 2.3).

Results on households' direct carbon emissions highlight strong decoupling with income. Macro-micro simulation, however, re-evaluates upwards the emission trajectories of official SNBC forecasts (Figure 2.2). Depending on energy savings variants, it computes households' direct emissions 37.3% to 52.6% below 2010 emissions in 2035 for the NZE scenario. In comparison, the SNBC trajectory forecasts a 68% decrease. Even the maximum energy savings variant leads to a delay of 3 to 4 years in

[17] Influence of the higher growth of capital income on income distribution in household surveys is limited by the under-reporting of income from capital and exceptional income common to all surveys (van Ruijven et al., 2015).

Table 2.3 – Evolution of disposable income components from 2010 to 2035

F4 Scenario	SNBC evaluation	Maximum energy savings	Median energy savings	Minimum energy savings
Wages	+42.2%	+41.6%	+41.3%	+40.9%
Capital income	+53.8%	+51.9%	+51.5%	+50.7%
Unemployment Benefits	+42.1%	+41.3%	+41.0%	+40.5%
Other Social Benefits	+49.5%	+49.1%	+48.8%	+48.5%
Foreign transfers	+53.4%	+55.9%	+56.2%	+57.2%
NZE Scenario	SNBC evaluation	Maximum energy savings	Median energy savings	Minimum energy savings
Wages	+45.4%	+44.0%	+43.3%	+42.9%
Capital income	+60.0%	+57.0%	+56.0%	+55.5%
Unemployment Benefits	+45.3%	+43.7%	+43.0%	+42.6%
Other Social Benefits	+49.0%	+48.3%	+47.8%	+47.5%
Foreign transfers	+37.4%	+42.1%	+43.0%	+43.4%

Note: Variations are from 2010 to 2035 on aggregate volumes of income (and not per capita) to be consistent with the growth of Real Disposable Income in Table 2.2. Carbon tax payments of households are rebated in proportion of income per consumption unit (see footnote 10).

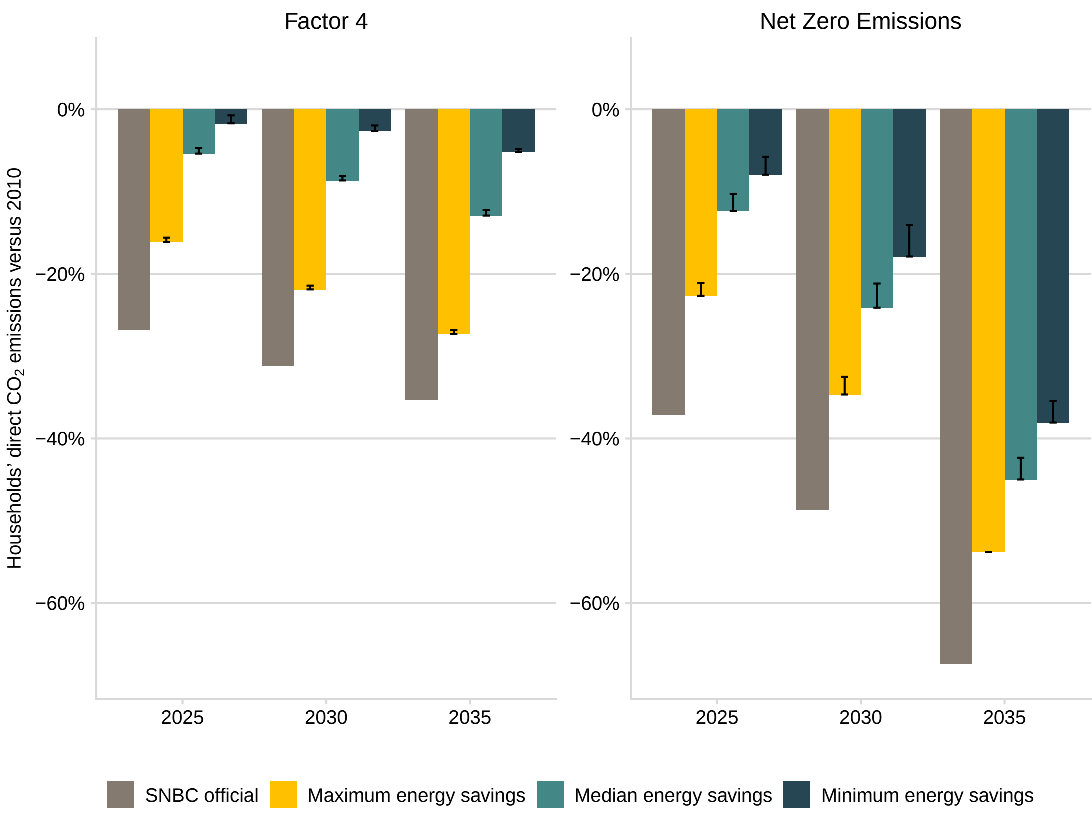
emission reductions that France would need to catch up during the 15 years separating 2035 from the 2050 carbon neutrality horizon. The higher emissions are despite the lower projected activity levels (Table 2.2). Analysis reveals that the resulting gap is partly caused by overestimated average energy savings in SNBC and partly by lower price and higher income elasticities in our microsimulation than in official forecasts.

Lastly, we test the marginal influences of carbon taxation, EV bonuses and thermal renovation subsidies by removing them from the otherwise full NZE package — keeping them at F4 levels. This allows revealing that the 25-points additional reduction in households' 2035 direct CO_2 emissions between NZE and F4 — under maximum energy savings — is more than half due to the carbon tax increase, 25% due to additional EV bonuses and only 1% due to thermal renovation subsidies.[18] We stress that this is not a direct measure of EV and thermal renovation efficiency to decrease CO_2 emissions but the marginal impacts of the subsidies. The increase of support measures to electric vehicle adoption and thermal renovation has less impact on households' emissions — reduction of 6 points by 2035 — than the targeting of technology shifts on highest energy consumers — reduction of 14 points by 2035 compared to the median variant and of 22 points compared to the minimum variant. Carbon taxes remain the most effective tool[19] with a drop of 14.1 pts of households' emissions when raised from F4

[18]The remaining 24% primary lie in the higher share of biogas and biofuel in the NZE scenario and in the partial redundancy of the policy tools.

[19]We note that ex-post studies of carbon pricing show positive but often limited impact of isolated carbon pricing on national CO_2 emissions (Green, 2021; Shmelev and Speck, 2018) as well as the significant and persistent fall of households' emissions in the UK (Känzig, 2021). In this study, we can only compare households' emissions reduction in F4 to NZE or 2010.

Figure 2.2 – Evolution of households' direct CO_2 emissions



Note: The intervals indicated for all results except the official SNBC correspond to the emission reduction intervals obtained for five recycling options (see section 4.4). The central option is that of the absence of recycling. Households' direct CO_2 emissions are those from direct fuel consumptions for both residential and mobility purposes.

level to NZE level (see Fig 2.B.2 in Appendix 2.B).

4.2 NZE could increase income inequalities, poverty and carbon-tax inequalities

We present the inequalities induced by NZE and F4 policy packages in several orthogonal directions, firstly income inequalities, then vertical and horizontal 'expenditure' (carbon tax payments) inequalities. This section holds constant the hypothesis of maximising energy savings by selecting the largest energy consumers as beneficiaries of electric vehicle adoptions and thermal renovations. The investment-driven growth supplement from F4 to NZE results in higher income, especially for decile 1 (D1) and median (D5) living standards at all tested horizons (Table 2.4). However, when households are not rebated

Table 2.4 – Evolution of income distribution indicators

F4 scenario	2010	2025	2030	2035
Gini index	0.285	0.251	0.237	0.23
D1 (€2019)	10,873	12,800	13,658	14,592
D5 (€2019)	20,824	24,143	25,764	27,560
D9 (€2019)	37,873	43,689	46,631	49,859
Poverty rate	14.96%	14.77%	14.90%	15.33%
NZE scenario	2010	2025	2030	2035
Gini index	0.285	0.256	0.247	0.24
D1 (€2019)	10,873	12,817	13,682	14,662
D5 (€2019)	20,824	24,203	25,949	27,870
D9 (€2019)	37,873	43,988	46,352	50,751
Poverty rate	14.96%	14.70%	15.01%	15.12%

Note: Results are those under the assumption of maximum energy savings variant without recycling of carbon tax payments. The Gini index aggregates the distribution of income into one single indicator. A Gini index of 0 would describe a population in which all individuals earn the same amount when an index of 1 represents the opposite extreme of the entire national income captured by one single person. In this particular table, rather than decile averages, D1, D5 and D9 designate the annual living-standard thresholds, in 2019 euros, between deciles 1 and 2, 5 and 6, 9 and 10. D5 is thus the median living standard of households. Living standard is income per consumption unit as defined in footnote 10S. The poverty rate is the rate of households with living standard below 60% that of D5.

their carbon tax payments, NZE induces higher Gini indexes and intercentile ratios — D9/D1, D9/D5 and D5D/1 are systematically higher under NZE than F4 (Table 2.4) —, which means that the distribution of income is wider and more unequal under NZE than under F4. Analysis of NZE marginal variants maintaining either EV support or renovation subsidies at F4 levels under median or minimum energy savings variants, reveals second-order effects on income distribution only, mainly caused by small GDP variations.

Last on the income side of inequalities, the marked favourable time trends of Gini indexes or intercentile ratios in both scenarios do not prevent rising poverty rates.[20] Considering French demographic trends, a 0.2-point increase of the rate means an 18.1% increase of the number of people living in poverty. Interestingly, despite its higher median income and thus poverty threshold, NZE exhibits a poverty rate 0.2 points lower than F4. This result moderates the concerns raised by the other income inequality indicators.

Turning to indicators of expenditure inequalities, we focus our analysis on direct carbon tax payments. Carbon taxation is significantly stronger under NZE than under

[20]The positive Gini and intercentile ratio dynamics result from favourable indexing assumptions by official SNBC evaluations, which we replicate in IMACLIM-3ME. In particular, unemployment benefits are indexed on wages and other social transfers, including pensions, on productivity growth. We will not comment upon the induced marked downward trend. Rather, we will keep our focus on its variations between the F4 and NZE scenarios.

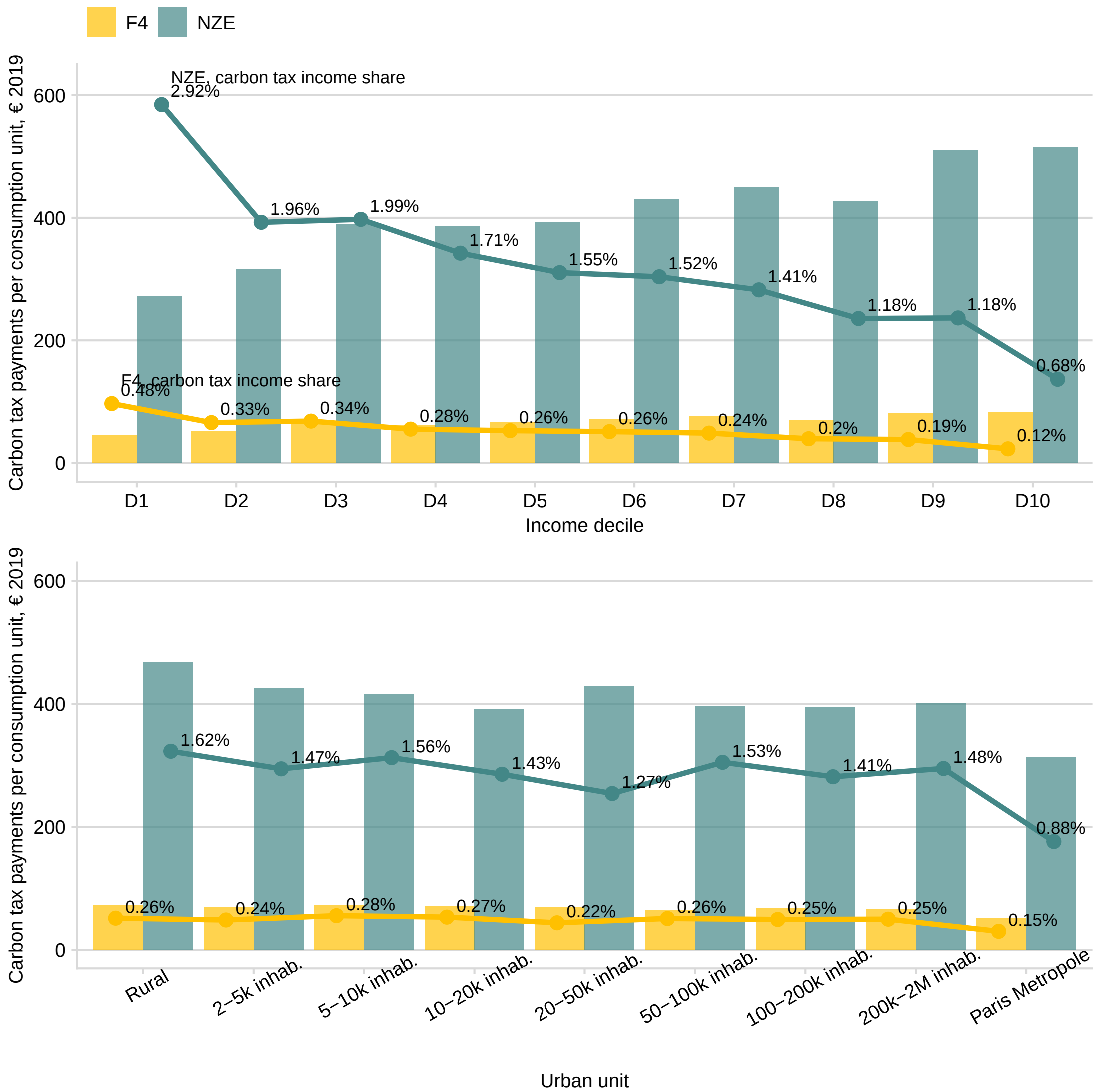
F4, up to ten times higher in 2035 (see Table 2.1). This signal prompts energy savings that mitigate the increases of vehicle and residential fuel and gas consumptions following the rises of income. Indeed, carbon tax payments in the NZE scenario are about 6 times higher than in the F4 scenario for all income deciles. The weight of carbon payments in households' disposable income increases similarly. The distribution of direct carbon tax payments is thus similarly regressive in both scenarios, inversely proportional to household income (Figure 2.3). Still, the rise of carbon tax payments can only amplify acceptability issues. In 2035, on average, D9 households dedicate €770 or 1.2% of their disposable income to carbon tax payments, while D1 households' payments of €350 mobilise 2.9% of their disposable income.[21] Regressivity stems from two preliminary observations that poorer households dedicate larger income shares to energy and are more dependent on energy goods. For instance, D1-D3 households have lower price elasticities for domestic fuels than richer households. Middle-class households (D5-D7) are more dependent on car fuel than richer households as price elasticities are U-shaped across income (see chapter 1). Like Ohlendorf et al. (2020) but contrary to Douenne (2020), we find that the regressivity of carbon tax payments is diminished when measured against expenditure rather than income, but persists from deciles 3 to 10 (see Appendix 2.G). Our results are thus robust enough to the choice of income or expenditures as a measure of economic standing.

Poterba (1991) and subsequent articles (see Cronin et al. (2019) and Metcalf (2019) for instance) apply the permanent income theory (Friedman, 1957) and use expenditures as a proxy for lifetime income. Their main argument is that annual income can fluctuate and does not include the use of loans or savings for retired persons and students especially. This approach has been criticised among others by Chernick and Reschovsky (1997) and Teixidó and Verde (2017), who contest both that expenditures are a constant fraction of lifetime income, and that gasoline and energy consumption decisions are made on the basis of lifetime income. Independent of the debate over the drivers of gasoline consumption, we believe that annual income is a more accurate proxy for households' acceptability of the carbon tax, especially considering the uncertainty surrounding the low-carbon transition. Hence, we prefer income to expenditures to compute the relative burden of carbon taxation for households.

Regarding horizontal inequalities, rural households pay more carbon tax because of longer daily journeys, mostly by private car, and larger dwellings. Carbon tax payments decrease with area density. NZE aggravates the divide between rural and urban households: profiles of payments and income shares along urban unit are more contrasted under NZE than F4. Rural households pay between 9.7% and 61.6% more than other households under NZE versus 3.9-53.4% more under F4. The effect in terms of share of disposable income and per consumption unit is less sharp, as households of the first income deciles live in denser areas and rural households are more populated (Figure 2.3).

[21] €770 and €350 are average payment per households, per consumption unit payments are respectively €511 and €272 for D1 and D9.

Figure 2.3 – 2035 carbon tax payments (bars) and their ratios to income (line) per decile



Note: Results are those under the assumption of maximum energy savings without recycling of carbon tax payments. Reading: on average, direct carbon tax payments of D1 households in 2035 are €45 per consumption unit and mobilise 0.48% of their disposable income in the F4 scenario, versus €272 per consumption unit and 2.92% of their income in the NZE scenario. Rural households dedicate 1.62% of their disposable income to carbon tax under NZE, 0.14 points more than 200k-2M city dwellers. Income deciles are defined in footnote 10.

The size of urban units is the main source of carbon tax payment discrepancy between households with similar income (Figure 2.4), which is consistent with the literature (Douenne, 2020; Fischer and Pizer, 2017; Pizer and Sexton, 2019). Intra-decile gaps exceed inter-deciles differences at least for the first 6 income deciles.

The type of housing is largely correlated with the size of urban unit, as 95% of rural dwellings are individual dwellings, while 67% of dwellings in agglomerations of more than 100,000 inhabitants are collective dwellings. Payments of households in individual housing remain higher than those of households in collective housing for all deciles. Disparities between regions are more complex. Regions with the coldest winters (East, West and North have the highest heating and hot water expenditures in 2010) do not induce systematically higher carbon tax payments. Indeed, rich households in these cold areas benefit from energy renovations under the assumption of maximum energy savings, as they are among the highest energy consumers (see section 3.3).

4.3 Electric vehicle and renovation subsidies distribution mitigates rural-urban divide and impacts emissions dynamics

The higher renovation and electric vehicle subsidies of the NZE scenario have only second-order effects on income distribution, thus have little impact on the Gini index, intercentile ratios or the poverty rate. However, they directly impact energy expenses, hence carbon tax payments (Figure 2.5): EV measures lower carbon tax payments the most, up to 16% for D4-D7 households, while renovation support reduces them by 2% at most for rich households in large cities. Carbon taxation remains regressive, but households' payments relative to income increase less than the tax. This reduced burden reflects the adaptation measures taken by households, as well as the impacts of additional measures to support thermal renovation and electric vehicles.

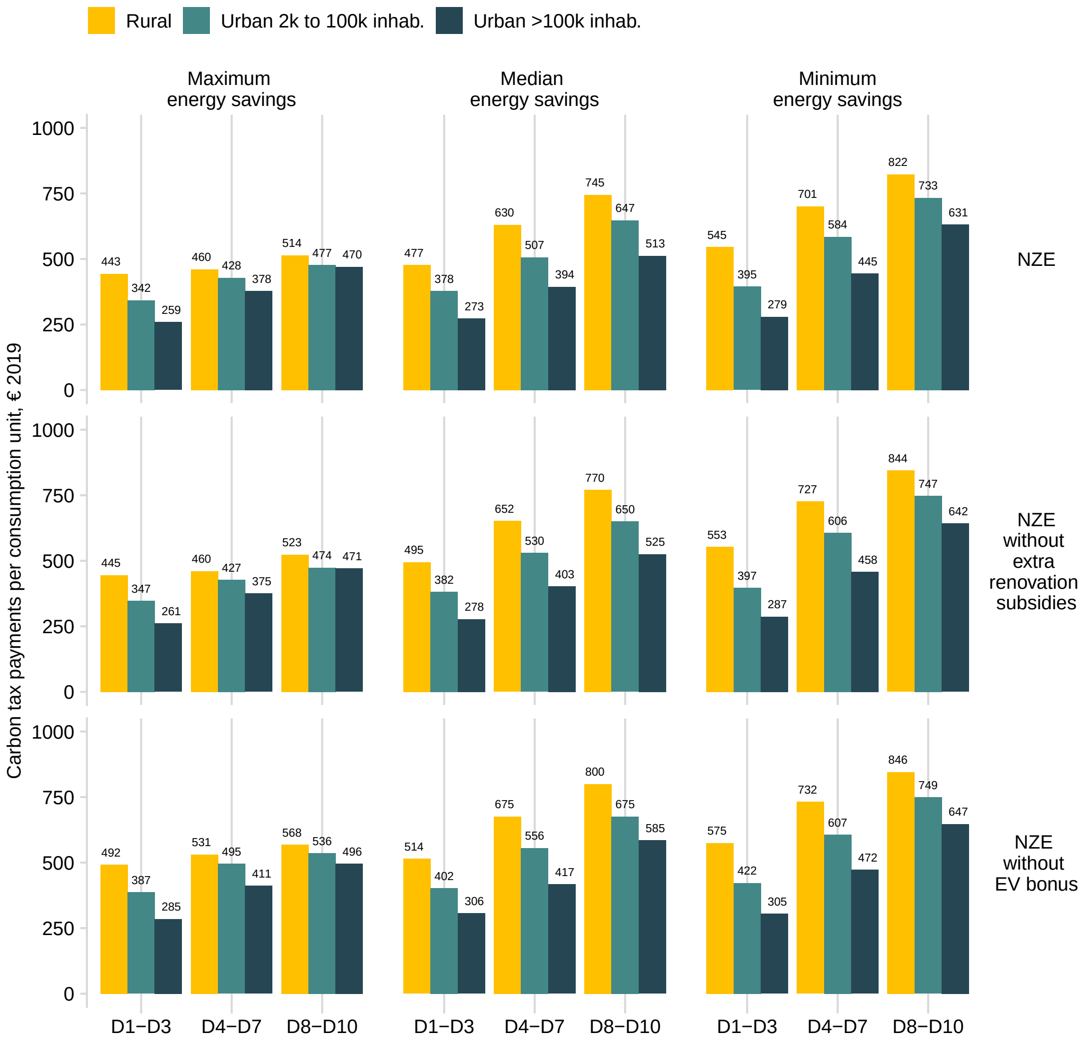
Selecting the largest energy consumers for EV adoption and thermal renovation increases vertical inequalities with or without an increase of EV and renovation support. For instance, in the full NZE scenario, D8-D10 rural households pay only 15.9% more than D1-D3 rural ones under maximum energy savings, against 50.8% under minimum energy savings (Figure 2.5). The more even distribution of payments across income deciles implies more unequal ratios to disposable income. This points at an efficiency-equity trade-off. Assuming that EV adoptions and thermal renovations benefit the highest energy consumers — maximising energy savings — favours rich and middle-class households while maximising emission reduction, whereas assuming that they benefit the lowest energy consumers decreases vertical inequalities but is suboptimal for emission reduction.

Conversely, assuming that EV and renovations benefit the highest energy consumers reduces horizontal inequalities. Under minimum energy savings and for the full NZE package, D4-D7 rural households pay on average 20% and 58% more carbon tax than D4-D7 urban households of respectively small and large cities. Under maximum energy savings, payment gaps are brought down to 7% and 22%.

Figure 2.4 – Horizontal inequalities in 2035 carbon tax payments under NZE scenario

Note: Results are those under the assumption of maximum energy savings without recycling of carbon tax payments. Payments are average annual payments per consumption unit (see footnote 10), in 2019 euros. For reasons of simplicity, results are aggregated on three income categories and three strata of urban unit (rural, urban in small and medium towns under 100k inhabitants and urban in cities above 100k inhabitants). Income deciles are defined in footnote 10.

Figure 2.5 – Impacts of EV and renovation support measures on carbon tax payments in 2035



Note: Results are those under the assumption of maximum energy savings without recycling of carbon tax payments. Reading: Vertical comparison highlights the 'volume' effect of subsidies by reporting mean carbon tax payments of three household categories for the NZE scenario, NZE with F4 EV bonus and NZE with F4 renovation subsidies. Horizontal comparison highlights the 'selection effect' through three energy savings options. Income deciles are defined in footnote 10.

The paradoxical effects of EV and renovation support measures are because the selection of beneficiaries has a weaker effect on poor households than on rich ones, but one more differentiated according to territory. In the full NZE scenario, maximum rather than minimum savings lower payments by 37.5% for rural D8-D10 households and 25.6% for large-city D8-D10 households, compared with respectively 18.8% and 7.1% for D1-D3 households. Importantly, the volume of subsidies is not nearly as significant as the selection. The two scenarios with limited volumes of renovations or EVs — due to lower subsidies — but well-targeted at energy-intensive households reduce more carbon tax payments and both vertical and horizontal payment inequalities than the full but poorly-targeted NZE package (Figure 2.5).

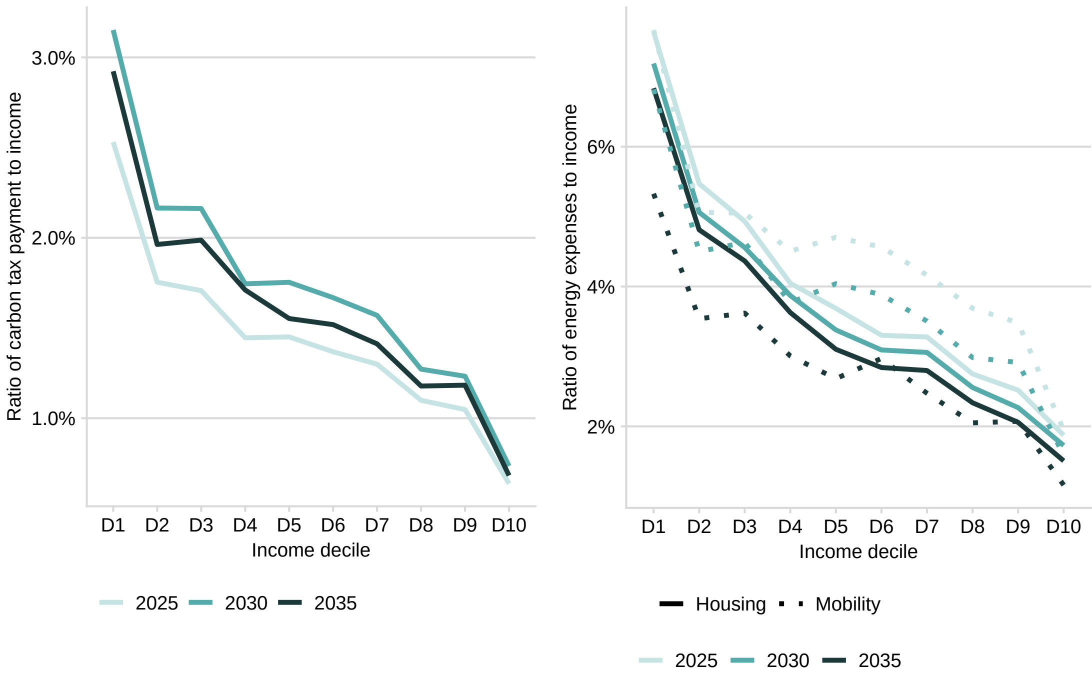
Average carbon tax payments across all deciles decrease from €600 in 2030 to €585 in 2035 (euros 2019) under full NZE and maximum energy savings. The curbing down is allowed by about one-third of households, who manage to decrease their payments between 2030 and 2035, by 27.0% despite the 38% increase in the carbon tax over the same period (from €178 to €246/tCO_2). 69% of these households, whose payments decrease between 2030 and 2035, have benefited from either EV adoption, thermal renovation or new efficient housing. The average payment also decreases under median energy savings but not under minimum savings, which demonstrates again the importance of adequate targeting of technology adoptions.

Reduced average payments imply more reduced average income shares dedicated to payments considering income growth. In fact, carbon payments decrease for all deciles and especially for the middle classes (Figure 2.6, left). The trend is explained by simultaneous decreases of households' energy efforts, especially for mobility with a drop of more than one third for the middle classes D4-D7 (Figure 2.6, right). This illustrates the efficiency of gradual EV penetration in reducing energy expenses, carbon payments and thus carbon emissions.

Low-income classes are the main beneficiaries of renovation under both maximum and minimum energy savings over time (Table 2.5). In 2035, the distribution of EVs among households forms an inverted U-shaped curve across income under maximum energy savings, even though richer households are better off in the short term. Minimum energy savings favour the poorest households (D1-D3). Subsidy volumes — which increase EV sales and renovations — have little effect on the evolution of this distribution. But, over time and the greater the volume, households selected by one or the other options tend to be the same, which reduces differences between energy savings variants.

Social acceptability of the NZE transition is called into question, particularly because of the rapid increase of carbon payments in the NZE scenario, which hits all households. Energy-efficient technologies prove efficient in reducing territorial inequalities for middle classes in the long run, but leave unprotected the poorest households, especially in urban areas. Consequently, investing in a greater volume of subsidies for EVs and renovation does not appear to be a short-term solution to policy impact mitigation, as it only allows for significant decreases of energy expenses between 2030 and 2035. The transition period 2025-2030 is therefore critical for the acceptability of a more ambitious strategy. EV and renovation subsidies need to be paired with

Figure 2.6 – Weight of carbon tax and energy in income under NZE scenario



Note: Results are those under the assumption of maximum energy savings without recycling of carbon tax payments. Differences between territories, which are lesser than for absolute payments, are not reported. Mobility energy expenses include EV electricity. Income deciles are defined in footnote 10.

Table 2.5 – Beneficiaries of energy-efficient technologies across time in the NZE scenario

	Maximum energy savings			Minimum energy savings		
Electric Vehicles	D1-D3	D4-D7	D8-D10	D1-D3	D4-D7	D8-D10
2025	13%	38%	49%	42%	32%	26%
2030	15%	42%	43%	40%	35%	26%
2035	21%	47%	32%	39%	40%	21%
Thermal renovations	D1-D3	D4-D7	D8-D10	D1-D3	D4-D7	D8-D10
2025	31%	40%	29%	39%	39%	22%
2030	33%	41%	26%	38%	40%	22%
2035	35%	41%	24%	37%	41%	22%

Reading: in 2025 and under maximised energy savings, (1) households owning electric vehicles are for 13% D1-D3 households, for 38% D4-D7 households and for 49% D8-D10 households; (2) households living in thermally renovated dwellings are for 31% D1-D3 households, for 40% D4-D7 households and for 29% D8-D10 households. Percentages may not sum to 100% due to rounding. Income deciles are defined in footnote 10.

some short-term policy targeting the burden of low-income households to ensure the acceptability of the tax.

4.4 Carbon payment recycling is complementary to subsidies in the short term

Social acceptability of environmental policies hangs on a sense of justice, i.e. the fair distribution of the burden among actors and the adequacy of means and ends (Douenne and Fabre, 2020). Recycling of carbon tax payments as a short-term solution addressing vertical inequalities has already been investigated and proven effective (Baranzini et al., 2017; Cronin et al., 2019). Direct transfers have been proven more equitable than, for instance, labour tax cuts (Fremstad and Paul, 2019; Klenert et al., 2018), especially when directed to poor people (Vogt-Schilb et al., 2019).

We test four direct compensatory policy options through rebates of carbon tax payments:[22,23]

- Per-capita rebate: each household receives an identical fraction per consumption unit (CU) of the collected tax. Because total energy expenditures increase with living-standard deciles, households in the lower deciles receive more rebate than they pay taxes.
- Poverty-targeted rebate: the rebate per CU is identical for households of the same decile, but higher for low deciles than for high ones. It is calibrated to at-least compensate 95% of decile 1 households prior to any adaptation behaviour, and is degressive at constant rate for the following deciles up to decile 9. Decile 10 households are excluded from compensation.
- Rural-targeted rebate: following on section 4.2 results that urban size is a better indicator of carbon payments than income, the rebate per CU is identical for households of same urban-density strata and skewed in favour of rural households. It is designed to at-least compensate 95% of rural households prior to adaptation, which leads to massive overcompensation for most of them due to the wide dispersion of energy consumptions of rural households.
- Living-standard rebate: each household receives an amount proportional to its living standard (disposable income per CU). This scheme neutralises the impact of rebating on income distribution.

[22] Our recycling terms are deliberately schematic and based on easily observable variables. We acknowledge the fact that any policy aimed at households supposes implementation costs that can potentially determine its efficiency. That is why we only consider variables simple enough to be the conditions of public policies: income, number of persons in the household and density of place of living.

[23] We choose to address inequalities by means of a social transfer additional to existing transfers, an option that is both likely to win the support of households for the necessary reforms, and easier to implement and less harmful to the carbon price signal than some targeted pricing options.

Table 2.6 – Impacts of four carbon tax recycling schemes on growth and income distribution under NZE

Variable	Horizon	Poverty-targeted rebate	Per capita rebate	Living-standard rebate	Rural-targeted rebate	No recycling
Macroscopic variables						
GDP vs 2010	2035	+48.1%	+47.4%	+47.4%	+47.4%	+46.7%
Unemployment rate vs 2010	2035	-0.01 pts	+0.31 pts	+0.30 pts	+0.32 pts	+0.63 pts
Household CO_2 vs 2010	2035	-51.8%	-52.5%	-53.2%	-52.4%	-53.7%
Income distribution						
Gini Index	2025	0.249	0.253	0.257	0.253	0.256
Gini Index	2030	0.237	0.242	0.246	0.243	0.247
Gini Index	2035	0.232	0.236	0.24	0.236	0.24
D1 (€2019)	2035	15,495	15,122	14,875	15,066	14,662
D5 (€2019)	2035	28,278	28,380	28,239	28,319	27,870
D9 (€2019)	2035	51,102	51,516	51,545	51,275	50,751
Poverty rate	2035	13.9%	14.7%	15.0%	15.1%	15.1%

Source: Authors' calculations. Gini index, deciles and the poverty rate are defined as in Table 2.4

Following the official low-carbon strategy, we assume full recycling of firms' carbon tax payments into tax credits.[24] Likewise, we fully rebate to households their own payments levied on direct fossil fuel consumptions. We focus our exposition on the NZE scenario for the maximum energy savings variant, where the higher carbon tax induces more direct inequalities but also more compensation possibilities.

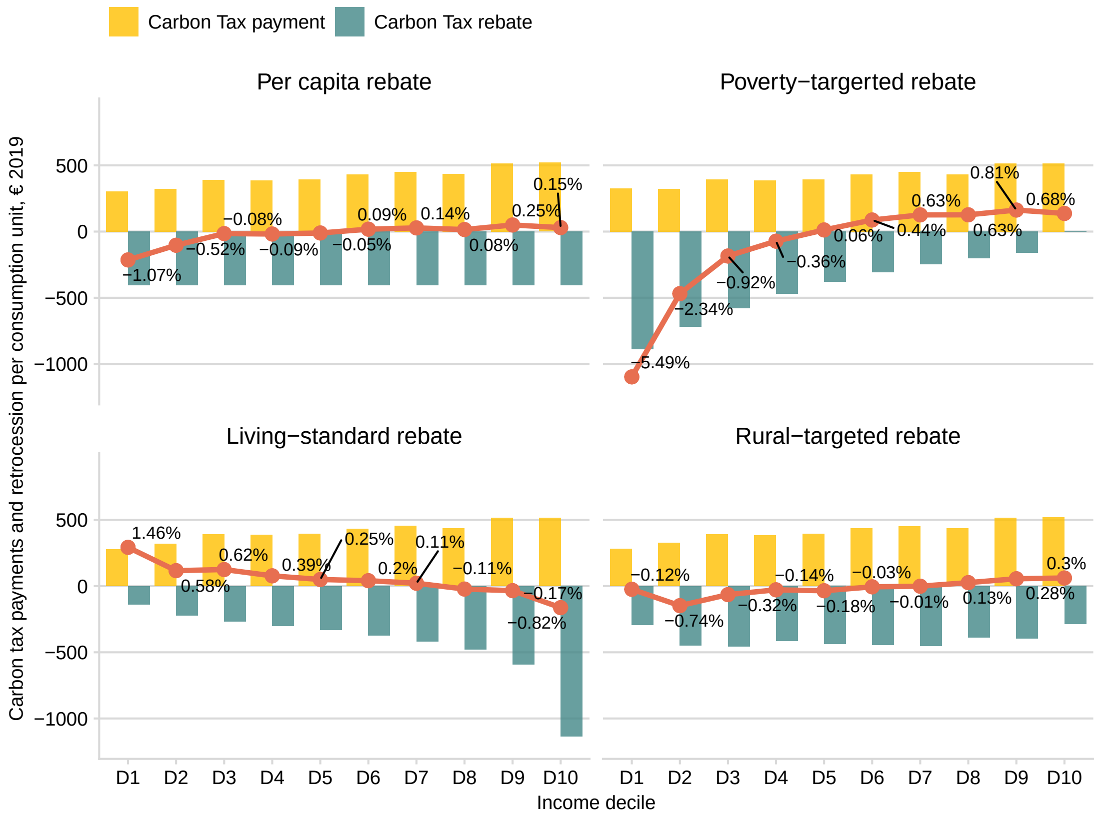
In 2035, the rebating of nearly 31 billion euros (€2019) to households boosts consumption and GDP growth (Table 2.6).[25] Per the loop architecture of our method, the targeting of recycling has significant macroscopic consequences. The poverty-targeted rebate maximises GDP growth, one percentage point ahead of per-capita rebate, at the cost of a 3.2% rebound in direct households' emissions compared to no recycling. Poorer households have higher income-elasticities in labour and carbon-intensive goods, thus sustaining both activity and emissions. Nevertheless, rebound effects due to rebating have much less influence on emissions than the selection of EV and renovation beneficiaries (see Figure 2.2).

Per-capita and poverty-targeted rebates are the only options making the net carbon tax progressive (Figure 2.7), with respectively 81% and 69% of D1-D3 households being at least compensated. Income distribution indicators are expectedly improved by the rebates favouring the poorest. By construction, the rebate proportionally to living standards leaves the Gini index and inter-decile ratios almost unchanged compared to the

[24]Additionally recycling part of households' payments to firms could increase economic activity with indirect benefits to households of higher deciles, while rebates to households could be focused on lower ones (Combet et al., 2009).

[25]Rebating options do not have as much influence in F4 due to the lower tax payments (4.7 billion 2019 euros in 2035 under maximum energy savings).

Figure 2.7 – 2035 carbon tax payments and rebates under NZE for four rebating schemes



Note: Results are those under the assumption of maximum energy savings. Reading: For each decile, the average 2035 carbon tax payments (yellow) and rebates (green) are plotted under four recycling schemes for the NZE scenario. The red line marks the ratio of net carbon tax (payment minus rebate) to income for each decile. Income deciles are defined in footnote 10.

absence of recycling. The poverty-targeted rebate allows NZE to have a Gini comparable to that of F4 (0.232 compared to 0.230), lower intercentile ratios and a poverty rate that is almost one point lower than in 2010. This confirms that it is possible to have a more ambitious yet fairer transition through the poverty-targeted recycling of carbon tax revenues.

The rural-targeted rebate largely reduces the territorial divide between rural and urban dwellers. Still, it concentrates overcompensation on a smaller number of households, with less than half (49.4%) of D1-D3 households compensated beyond their carbon tax payments. It disproportionately benefits rural people with an annual 2035 carbon tax rebate of more than €2000 per household when the payment differential between rural and large-city dwellers is only €150-300 without recycling. Induced income inequalities are comparable to those induced by per-capita rebate: inequalities are reduced compared to the absence of recycling, but are increased compared to poverty-targeted rebate and therefore worse than in the F4 scenario. The rural-targeted rebate should not be used to limit inequalities but can easily be coupled with another recycling scheme if warranted by the concentration of opposition to the low-carbon transition in rural areas.

The poverty-targeted rebate is complementary to EV and renovation support measures as it cuts carbon tax payments in the short term. Following Farrell (2017) or Douenne (2020), to further interpret results we regress net-of-rebate carbon tax payments for three schemes and the no-recycling option for NZE in 2025 (Table 2.7). 2025 is the short-term interest horizon where we seek to establish the complementarity of the policy tools to ensure social acceptability. Poverty-targeted recycling considerably increases the weight of disposable income in the payment, thus making it more progressive. It also reduces territorial inequalities: the "rural" dummy variable is no longer significant and lower than without recycling, at the cost of a slight increase in the gap between small and large cities.

EV adoption for rural dwellers means a drop of around €400 under maximum energy savings compared to €650 under minimum energy savings. EV influence is roughly similar for no-recycling, and income-related recycling. Renovations reduce carbon payments (negative coefficients), but their influence is not significant enough to compare scenarios under maximum energy savings. We conclude that recycling and EV and renovation support measures are complementary in the short term since supported technologies contribute to lowering carbon payments in similar proportions regardless of the recycling scheme. Poverty-targeted rebates effectively compensate the first deciles to the point of making the carbon tax progressive, decreasing poverty and income inequalities without increasing territorial disparities.

5 Conclusion & policy implications

We have assessed the distributive effects of two environmental policy packages of incremental ambition: The French Stratégie Nationale Bas Carbone (SNBC) 2015 and 2020 editions aiming respectively at cutting 1990 emissions by 75% (Factor Four, F4) and reaching Net Zero Emissions (NZE) by 2050. We linked macroeconomic modelling to microsimulation through iterative exchange of shared variables to represent macro- and microeconomic effects of disaggregated household behaviour and explicit penetration of electric vehicles and thermal renovations.

Our first conclusion is that low-carbon strategies — either F4 or NZE — induce regressive carbon tax payments and income impacts if they do not consider recycling of the carbon tax revenues. Our modelling method integrates all effects pointed out as progressive by the literature: income effects (Rausch et al., 2011), indexation of social income on prices (Metcalf, 2019), use of multisector macroeconomic modelling (Ohlendorf et al., 2020), subsidies for low-carbon technologies and the crossed effect

Table 2.7 – Regression of net carbon tax payment per household in 2025

	Dependent variable: Net carbon tax payment							
	No rebate		Poverty-targeted rebate		Per-capita rebate		Rural-targeted rebate	
	(Max)	(Min)	(Max)	(Min)	(Max)	(Min)	(Max)	(Min)
Intercept	$-1{,}077.49^{***}$	$-1{,}563.38^{***}$	$-6{,}041.20^{***}$	$-7{,}502.50^{***}$	-842.84^{***}	$-1{,}156.83^{***}$	-588.49^{***}	-793.66^{***}
	(113.55)	(136.20)	(140.61)	(175.12)	(118.73)	(143.33)	(132.61)	(157.68)
log(income)	126.55^{***}	160.60^{***}	653.03^{***}	790.53^{***}	102.32^{***}	119.26^{***}	130.10^{***}	145.34^{***}
	(11.41)	(13.66)	(14.08)	(17.54)	(11.91)	(14.35)	(13.35)	(15.83)
Consumption units	137.07^{***}	186.35^{***}	-660.74^{***}	-762.09^{***}	-245.10^{***}	-259.43^{***}	-256.58^{***}	-270.95^{***}
	(14.08)	(16.76)	(17.06)	(20.79)	(14.60)	(17.45)	(16.34)	(19.37)
Rural (dummy)	119.25^{***}	164.57^{***}	72.65^{***}	116.02^{***}	109.80^{***}	157.40^{***}	$-1{,}969.50^{***}$	$-2{,}356.72^{***}$
	(19.44)	(22.89)	(23.44)	(28.18)	(19.99)	(23.79)	(22.45)	(26.28)
Small city (dummy)	82.36^{***}	96.09^{***}	63.02^{***}	70.96^{***}	77.57^{***}	91.31^{***}	-315.42^{***}	-373.78^{***}
	(17.66)	(20.72)	(21.32)	(25.47)	(18.17)	(21.50)	(20.37)	(23.88)
Age	-2.76^{***}	-0.33	-4.23^{***}	-2.15^{***}	-2.79^{***}	-0.34	-1.15^{**}	2.00^{***}
	(0.40)	(0.47)	(0.48)	(0.58)	(0.41)	(0.49)	(0.46)	(0.54)
Region	7.02^{***}	1.40	4.84^{*}	-1.22	6.21^{***}	0.33	5.53^{**}	-1.15
	(2.24)	(2.67)	(2.71)	(3.29)	(2.32)	(2.77)	(2.59)	(3.08)
Surface	2.13^{***}	3.58^{***}	3.33^{***}	5.03^{***}	2.37^{***}	3.79^{***}	1.97^{***}	3.45^{***}
	(0.15)	(0.18)	(0.19)	(0.22)	(0.16)	(0.19)	(0.18)	(0.21)
Electric Vehicle (EV)	30.37	-368.20^{***}	152.29^{*}	-393.17^{***}	21.73	-401.09^{***}	222.27^{***}	-327.64^{***}
	(71.20)	(68.12)	(84.94)	(84.02)	(73.14)	(71.04)	(83.96)	(78.58)
Rural×VE	-408.86^{***}	-267.01^{**}	-460.45^{***}	-244.25	-416.51^{***}	-248.05^{**}	-937.20^{***}	-261.39^{*}
	(89.63)	(121.32)	(107.36)	(149.64)	(92.32)	(125.41)	(103.46)	(140.84)
Small city×EV	-197.38^{**}	-90.77	-274.28^{**}	-153.41	-198.86^{*}	-75.03	-482.15^{***}	-56.69
	(99.68)	(110.25)	(120.86)	(135.43)	(103.37)	(114.66)	(118.21)	(127.18)
Thermal Renovation (TR)	8.46	-222.42^{***}	-7.35	-263.37^{***}	23.05	-237.57^{***}	27.24	-287.75^{***}
	(26.26)	(31.61)	(31.77)	(40.13)	(27.64)	(32.96)	(30.50)	(37.25)
Rural×TR	-21.28	-18.29	-26.80	-10.90	-37.14	-7.80	28.86	145.07^{***}
	(38.12)	(46.86)	(46.26)	(58.50)	(39.95)	(48.68)	(44.32)	(54.49)
Small city×TR	-57.34	-46.68	-92.23^{**}	-71.35	-66.73^{*}	-43.13	-62.36	-75.82
	(37.19)	(46.30)	(45.08)	(58.10)	(38.99)	(48.19)	(43.10)	(53.99)
New Housing (NH)	75.17^{**}	-252.82^{***}	112.75^{***}	-215.04^{***}	67.41^{*}	-255.67^{***}	132.51^{***}	-321.21^{***}
	(35.73)	(36.69)	(43.21)	(45.33)	(37.01)	(38.16)	(41.86)	(42.22)
Rural×NH	72.05	-20.37	17.56	-107.38	75.63	-24.82	8.05	88.30
	(51.93)	(56.70)	(62.81)	(70.05)	(53.81)	(58.88)	(59.89)	(65.85)
Small city×NH	-31.62	-45.37	-53.73	-77.08	-31.33	-48.89	-36.03	-112.30
	(53.12)	(59.94)	(64.11)	(73.64)	(54.95)	(62.20)	(62.28)	(68.86)
Observations	10,251	10,251	10,261	10,262	10,256	10,257	10,254	10,255
Adjusted R^2	0.12	0.19	0.26	0.29	0.06	0.11	0.57	0.57

*p<0.1; **p<0.05; ***p<0.01

Note: The baseline of the size of urban unit is Large cities of more than 100,000 inhabitants. Some households have been withdrawn due to negative or zero disposable income. We observe likewise trends in NZE 2035 with no rebate, per capita rebate and rural-targeted rebate; redistribution effects under poverty-targeted rebate override most of the effects of EV and renovation support measures (see Appendix 2.H, table 2.H.4). Under minimum energy savings without rebate, adoption of an EV means a €635.21 decrease in carbon tax (-368.20+-267.01). The decrease is €408.86 under maximum energy savings.

with a carbon tax (Lamb et al., 2020). Contrary to Goulder et al. (2018), we conclude univocally that all these effects are not enough to offset the regressive impact of the carbon tax and the induced increase of poverty.

Our second conclusion is that targeting electric vehicle adoption, new efficient dwellings and thermal renovations on the largest energy consumers is essential to limit horizontal, especially territorial, inequalities, and to approach mitigation objectives. But such targeting advantages middle classes and richer households and thus widens vertical inequalities and carbon tax regressivity.

Thirdly, electric vehicles are particularly effective in both cutting down long-term carbon tax payments and reducing the rural-urban divide when benefiting the largest fuel consumers, thereby maximising energy savings. The progressive penetration of electric vehicles allows the average carbon tax payment to decrease after 2030.

Fourthly, recycling carbon tax payments through poverty-targeted or per-capita rebates reduces income inequalities and poverty and makes the carbon tax progressive in the very short term. However, both these direct "lump-sum" recycling options do not tackle horizontal inequalities and trigger rebound effects of about 3% of GHG emissions.

Fifthly, carbon tax recycling and electric vehicle and renovation support measures are highly complementary on the short term and are both needed for a successful energy transition. Rebating carbon tax payments to households does not limit the efficiency of subsidies but warrants that 81% of the three lowest income deciles are better off with the policy. Our study suggests that recycling could only be a temporary compensation until 2035, when household adaptation and diffusion of EV and thermal renovations have sufficiently lowered carbon tax payments.

We could refine our methodology in several directions: the growth of the six different income sources could be differentiated across sectors of activity and skill levels of workers to differentiate the labour income variations benefiting micro-simulated households. Additionally, we could better harmonise between our different data sources by, e.g., introducing hybrid accounting of economic and energy flows (Ghersi, 2015) or correcting the (under-reported) capital income of database households. Notwithstanding, the present analyses are clearly far from exhausting the potential of our numerical tool. The wealth of information of our household database calls for further investigation of the French energy transition, including beyond what the French government's official strategy proposes.

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Appendix

Un flux continuel de mille points noirs qui s'entrecroisaient sur le pavé faisait tout remuer aux yeux. C'était le peuple, vu ainsi de haut et de loin.

Victor Hugo, *Notre Dame de Paris*

2.A Economic vulnerability types

The procedure for establishing the typology of economic vulnerability is taken from Nadaud (2021). The first step is the principal component analysis (PCA) of the French Expenditures Survey ('Budget des Familles', BDF) data for 2010, which is our reference year. We carry out the PCA (Lebart et al., 2006) on the more than 10,000 metropolitan households in the 2010 BDF survey. We characterise each household by the distributions of its pre-committed (also known as constrained) expenditures and sources of income. Both income and pre-committed expenditures are described as shares (i.e. as percentages of total income and total constrained expenditure, respectively). Following Quinet and Ferrari (2008), pre-committed expenditures include energy and non-energy housing expenditures, telecommunications, television subscriptions, school canteen fees, insurance fees and financial services. Income sources are aggregated into labour income (employed and self-employed), social income (including pensions), property income, direct assistance from third parties and other miscellaneous income. We carry out the PCA on these twelve active variables, to which we add several dozen quantitative and qualitative socio-economic variables as illustrative variables (variables correlated with the results produced by the active variables for interpretation purposes).

The results of the PCA can be summarised as follows. On the first axis, labour income, associated with constrained housing expenditure excluding domestic energy and school canteen expenditure, is opposed to social income, correlated with expenditure on domestic energy and insurance. On the second axis, the opposition between labour income and social income is still present. Labour income is associated with expenditures on school canteens, telecommunications, financial services and insurance, and social income with expenditures on housing excluding domestic energy.

PCA results allow computing the input data for the household typology stage, which consists of household coordinates on the first two axes of the PCA. The first two axes are retained alone because they return 40% of the information contained in the table of correlations between sources of income and constrained expenditures, while the following axes only marginally increase the percentage of information returned. On the basis of the coordinates of households in the PCA, the typology stage consists of applying an automatic classification algorithm known as "hierarchical ascending" (Lebart et al., 2006), which results in the definition of four types. Detailed analysis of the socio-economic characteristics of types produces the following dominant profiles:

- Type I: young active tenants in large cities.
- Type II: retired, poor, single-person households tenants in large cities.
- Type III: well-off working people in access to property (with repayment of property loans).
- Type IV: retired, modest, rural and small town owner-occupiers.

The typology is one of economic vulnerability because it segments the population of households into homogeneous groups according to their dependence on social income or assistance associated with the burden of constrained expenditures, two factors that influence households' flexibility to face changes of economic context. The examination of expenditures and income structures shows that types II and IV, mostly composed of retired urban tenants and owner-occupiers, are the most economically vulnerable.

2.B Policy packages: Factor 4 versus NZE

The Stratégie Nationale Bas Carbone (SNBC) is France's roadmap for reducing its greenhouse gas emissions. The first edition of the SNBC was presented in 2015 and aimed at the fourfold reduction of greenhouse gas emissions by 2050, compared to 1990 (Factor 4). The second SNBC, published in April 2020, raises the country's mitigation objective to carbon neutrality (Net Zero Emission) by 2050. The SNBC presents the country's carbon budgets by 4-year period and details sectoral efforts necessary to abide by them.

Our study examines the distributional impacts of two climate policy packages as estimated by the ThreeME model in an official evaluation of the Low Carbon Strategy. For readers familiar with French low carbon policy, we specify that the NZE scenario (Net Zero Emission) corresponds to the official scenario known as "With Additional Measures" (Avec Mesures Supplémentaires, AMS), which targets carbon neutrality in 2050 as contribution to the global effort to limit global warming to 1.5°C. The Factor-4 scenario (F4) is known in French nomenclature as "With Existing Measures" scenario (Avec Mesures Existantes, AME). F4 aimed to reduce 1990 emissions by a factor of four by 2050, as part of a global mitigation effort limiting global warming to 2°C.

The two ThreeME forecasts of each scenario build on shared assumptions concerning demography and exogenous technical progress (labour productivity), which jointly define potential growth in the economy (see supplementary documents with IOT tables). Moreover, the ThreeME simulations include numerous scenario elements, which exogenously constrain both energy supply and demand trajectories in order to match the hypotheses of the French low carbon strategy (SNBC). In other words, the NZE scenario achieves carbon neutrality by construction in 2050. It only aims to evaluate the macroeconomic impact of the revised SNBC and not to validate the capacity of the Strategy's measures to achieve carbon neutrality.

The following sections summarise how the main assumptions underpinning the SNBC are translated in ThreeME forecasts (be they exogenous constraints or actual modelling results). We structure them according to four dimensions of decarbonisation: energy supply and carbon taxation, industry, transport and housing.

2.B.1 Energy mix and carbon taxation

The SNBC forecasts the evolution of energy supply and must therefore be compatible with the national plan for energy (PPE, 'Programmation Pluriannuelle de l'Energie'), revised in 2018, which sets the trajectory of the French energy mix. In particular, the costs of renewable energies and the energy consumptions of the production sectors and households align on the successive PPEs.

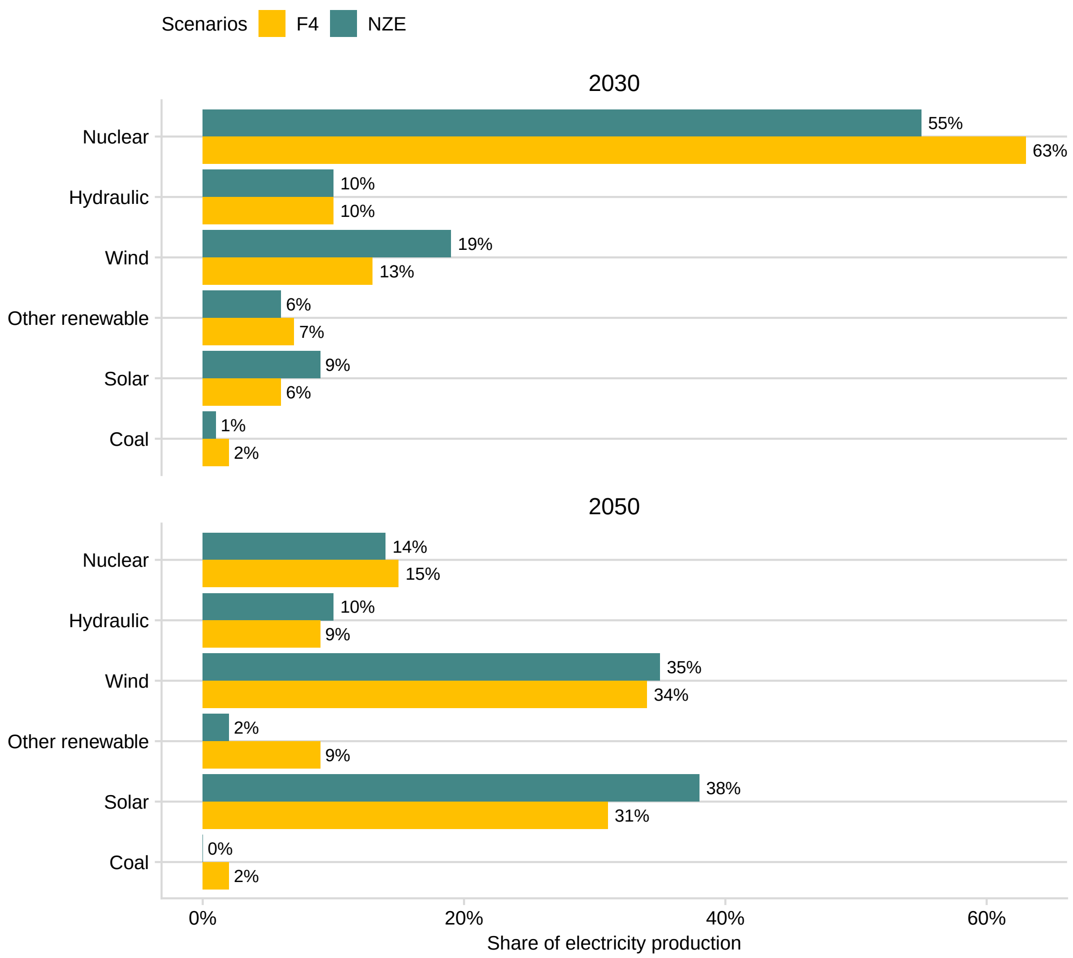
The NZE scenario thus plans to develop wind and solar power production. The share of nuclear power in electricity production is to drop from 75% in 2018 to 14% in 2050. NZE also projects the complete phasing out of coal from the electricity mix (Figure 2.B.1). NZE plans to replace fossil fuels using renewable sources. The objective is that 79% of fuels and 92% of network gas are from non-fossil sources (biofuels, biogas) in 2050. Under the F4 scenario, we assume a constant contribution of 2% of coal. The F4 scenario focuses on the electricity mix and maintains the input of non-fossil sources at current levels until 2050, i.e. 6% for biofuels and 0% for biogas.

Concerning energy demand, the SNBC plans increased carbon taxation to incentivise economic agents to reduce their emissions (Figure 2.B.2). The ThreeME simulations of both NZE and F4 scenarios assume that carbon tax proceeds are rebated to firms in the form of tax credits in proportion to turnover, and to households as lump-sum transfers. The NZE scenario foresees the gradual increase of the carbon tax: 114 €/tCO_2 in 2025 (in constant euros 2019), 177 €/tCO_2 in 2030, 246 €/tCO_2 in 2035 and up to 604 €/tCO_2 in 2050 (still in euros 2019). In comparison, the F4 scenario freezes the carbon tax at its 2019 level of 44.6 €/tCO_2 , which translates into 27 €2019/tCO_2 in 2035 and 18 €2019/tCO_2 in 2050.

2.B.2 Industry

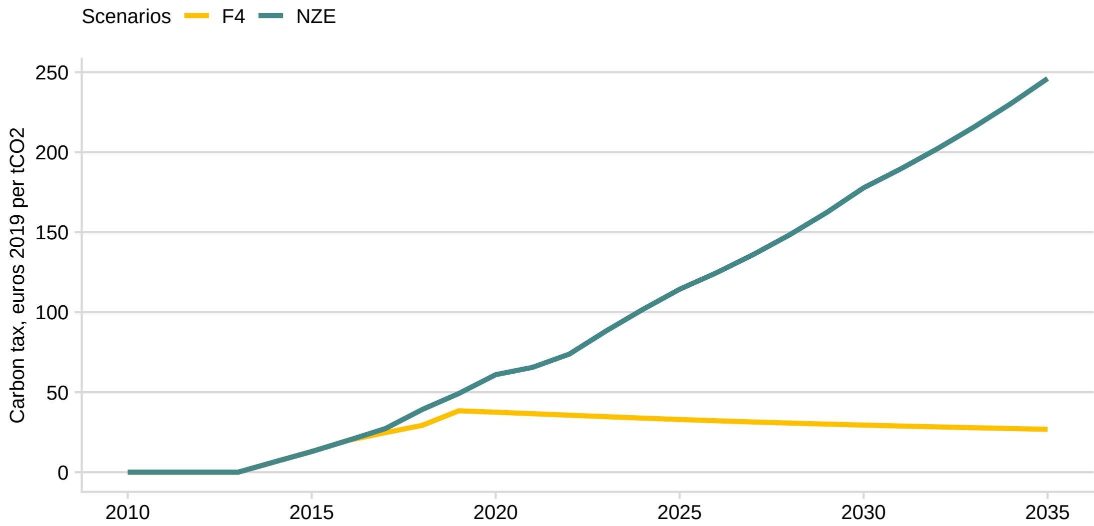
Decarbonisation of the productive sector comes from improving the energy efficiency of production and substituting electricity to fossil fuels. ThreeME models decarbonisation by taxing emissions, which both encourages the substitution of capital for energy and penalises the consumption of fossil fuels. Emissions result from the intermediate

Figure 2.B.1 – Electricity production mix under F4 and NZE scenarios in 2030 and 2050



Source: ThreeME, ADEME.

Figure 2.B.2 – Carbon tax trajectory under F4 and NZE scenarios



Source: ThreeME, ADEME.

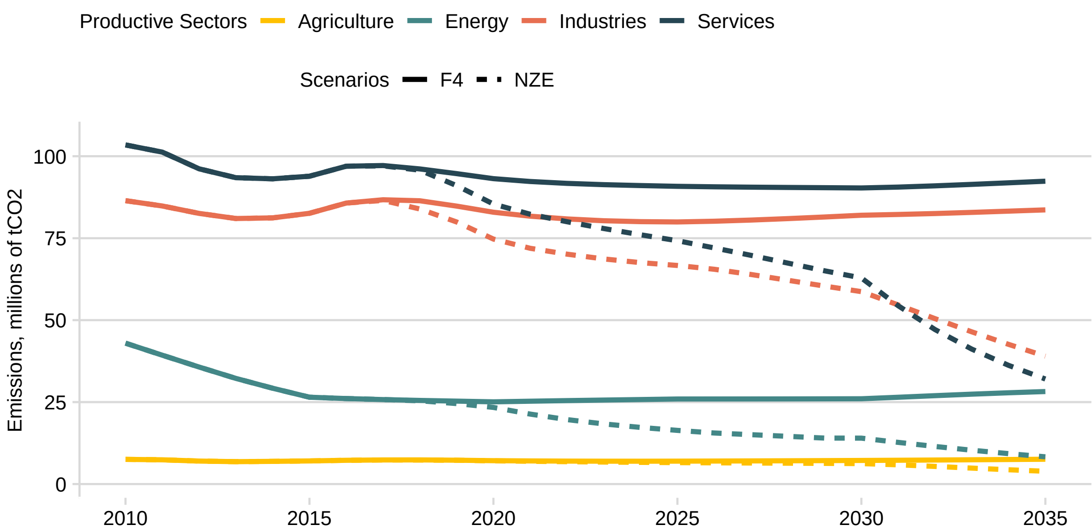
consumption of fossil fuels by each sector (Figure 2.B.3). The ratios of energy consumptions to outputs define the energy intensities of the 24 productions disaggregated by ThreeME. These intensities — also known as technical or Leontief coefficients — are also defined for non-energy inputs. We keep them constant at ThreeME levels for each scenario and each time horizon.

2.B.3 Transports

The SNBC aims to reduce transport emissions of both households and commercial activities for freight and passengers. It considers multiple levers: improvement of the energy efficiency of thermal engines in buses, trucks, ships and aircrafts; the substitution of electricity and gas for oil products in freight transport; and increased capacity investment in the rail sector, which should increase demand and encourage modal shift to rail for passengers and goods. Emissions from transportation sectors (air, rail, road and water) drop by 42.6% between 2010 and 2035 under the NZE scenario.

Concerning households, SNBC measures target private transport emissions through the combination of demand reduction, efficiency improvements and electrification. Demand reduction stems from increased working from home and infrastructure management (urban tolls, reduction of traffic lanes through the development of specific sites for public transport and non-motorised modes). It leads to a 22% drop of the average annual mileage of vehicles over 25 years, in both scenarios. Efficiency

Figure 2.B.3 – Emissions from productive sectors under F4 and NZE scenarios



Source: ThreeME, ADEME.

improvements reduce the fuel consumptions per km of conventional car by 32.0% between 2010 and 2035 in the NZE scenario, compared with 11.3% in the F4 scenario.

Finally, ThreeME projects that electric vehicles (EVs) will account for 49% of total vehicle sales in the NZE scenario in 2035, which will induce a 17% drop in sales of internal combustion vehicles compared to 2010. In comparison, the F4 scenario only projects EV sales to account for 24% of new vehicle sales in 2035 and a 9% drop in sales of internal combustion vehicles compared to 2010. EV penetration is incentivised by a bonus/malus policy in favour of less polluting vehicles (Table 2.B.1). On top of EV penetration, the policy encourages improvement of the efficiency of conventional alternatives. The F4 scenario relies on measures decided prior to July 1st, 2017. It encourages EV purchase with a bonus until 2023, then considers the progressive increase of the malus applying to the most polluting fossil-fuelled vehicles (class G) and the decrease of the bonus on efficient combustion vehicles (class A) (Table 2.B.1).

The strong penetration of EV under NZE is explained by the extension of this bonus policy to 2040. The long-term attractiveness of electric vehicles is ensured by a strong bonus/malus differential between the purchase of a fossil-fuelled vehicle and an electric vehicle: between €4,400 and €10,840 (2019 euros) difference for the purchase of a highly efficient fossil-fuelled vehicle (class A) and a highly polluting vehicle (class G), respectively. Indeed, NZE plans the end of all bonuses to fossil-fuelled vehicles — even the most efficient ones — in 2024 and increasing maluses over time.

Table 2.B.1 – Bonus and malus applied to vehicle purchases under F4 and NZE scenarios

2019 euros	2010	2025	2030	2035
F4 scenario				
EV Bonus	5,251	—	—	—
Bonus/malus to class-A fossil-fuelled vehicle	985	553	494	450
Bonus/malus to class-G fossil-fuelled vehicle	-2,561	-5,901	-5,273	-4,800%
NZE scenario				
EV Bonus	5,251	5,729	4,955	4,393
Bonus/malus to class-A fossil-fuelled vehicle	985	-144	-1,263	-2,572
Bonus/malus to class-G fossil-fuelled vehicle	-2,561	-6,437	-6,706	-7,398

Source: ThreeME, ADEME.

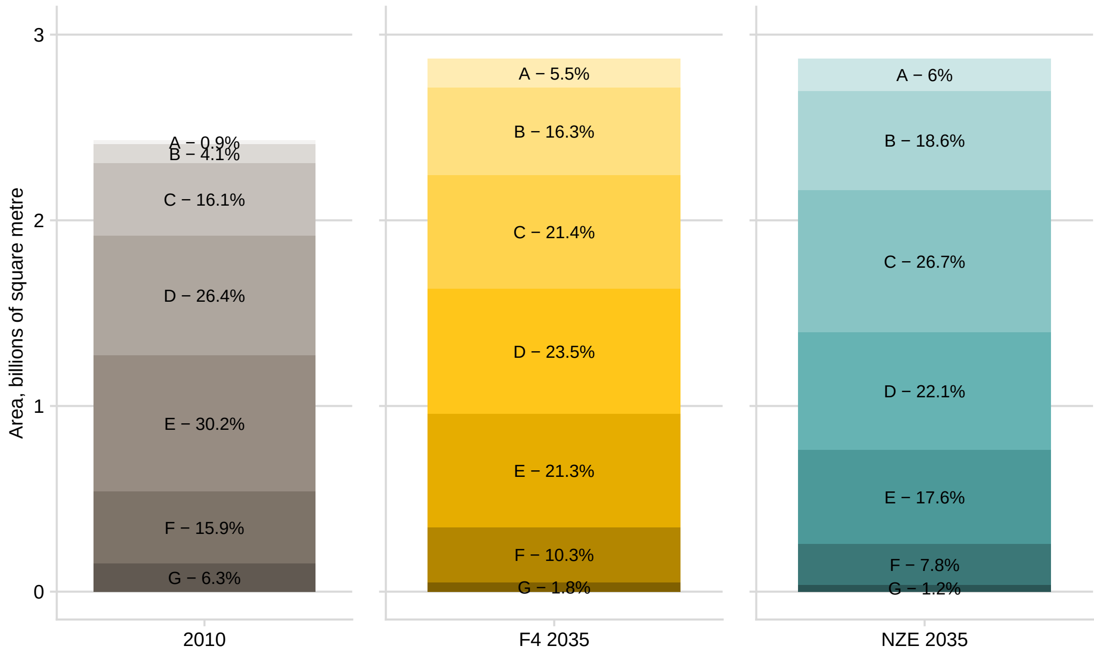
2.B.4 Housing

The SNBC applies different policy instruments to tertiary and residential buildings. For the tertiary sector, it enforces renovation obligations, which ThreeME translates into investments to reduce consumptions and emissions. For residential buildings, the SNBC supports the construction of new efficient housing and renovation of existing dwellings. On the one hand, dwellings built after 2019 must meet the requirements of energy performance diagnosis classes (EPD) A or B. On the other hand, renovations are subsidised through the Tax Credit for Energy Transition (CITE) up to 11.5% of the actual renovation costs (the official announcement of 30% tax credits relates to expenses net of labour costs). The F4 scenario ends this scheme in 2019, while NZE extends it to 2050.

The core of the low-carbon housing strategy is to eventually replace 'poorly efficient' dwellings (EPD E, F and G) by 'efficient' (EPD A and B) dwellings (Figure 2.B.4). The volume of efficient dwellings is multiplied by 6.4 under NZE (compared with 5.1 under F4) between 2010 and 2035. The volume increase proceeds from new housing for 58% and from housing renovation for 42%. The share of poorly-efficient dwellings in the stock falls by half from 52% to 24% under NZE (33% under F4) by 2035. As the destruction of housing remains marginal, the eradication of poorly-efficient dwellings is mainly based on sustained rates of renovations (Figure 2.B.5).

The technical assumptions underlying housing construction and renovation operations are identical in both scenarios. The ThreeME model indexes renovation costs per square metre to construction prices. Similarly, new housing prices follow construction prices without explicitly accounting for the additional costs generated by new energy efficiency regulations from 2019 onwards. Energy efficiency gains offset the investment costs of renovation for households. For example, on average over 2010-2035, class B dwellings consume about 91% less than class F dwellings of the same size.

Figure 2.B.4 – Structure of the housing stock by energy performance diagnosis in 2010 and 2035

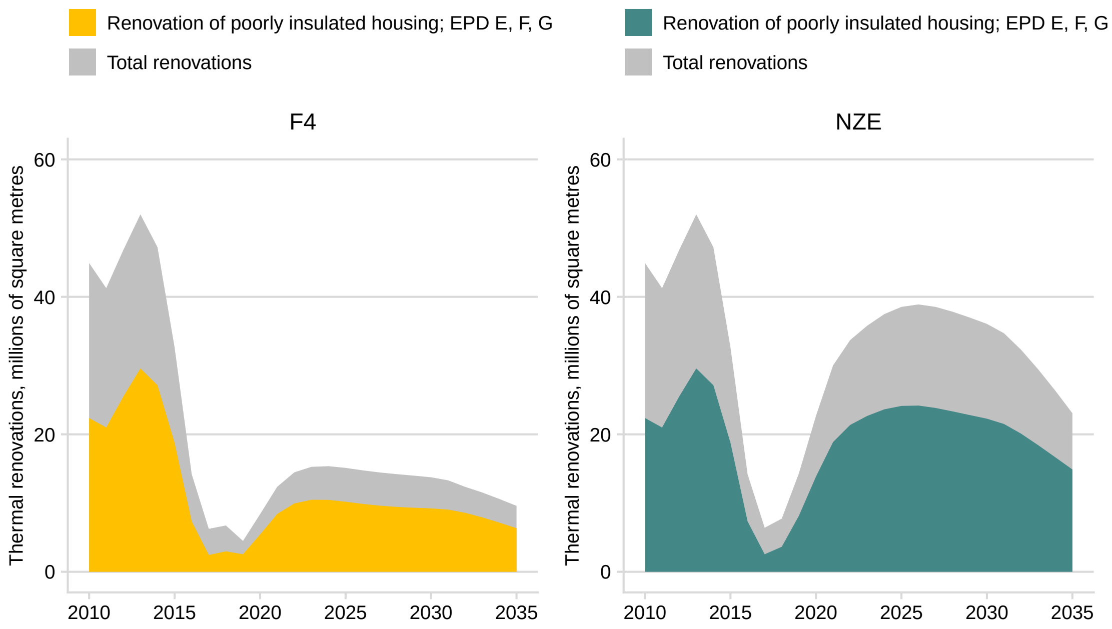


Source: ThreeME, ADEME.

The difference between the two scenarios NZE and F4 lies in the ambition of the volume of renovation. A little over one billion square metres are treated between 2010 and 2035 under NZE (the total stock is 2.5 billion square metres in 2020). The budget devoted to subsidies is substantial: 45 billion euros (2019 euros) over 25 years, with around 30 billion concentrated on later 2026-2035 efforts and only 16.5 billion paid over the sixteen years of 2010-2025. Under F4, renovation benefits about 500 million m2 despite the end of renovation subsidies in 2019. The renovated surface is thus only half that of NZE despite a 6-time lower subsidy total (7.6 billion over 2010-2035). The evolution of relative prices, including the effects of the relatively low carbon tax, therefore provides incentives for renovation, which the additional subsidies in the NZE scenario only reinforce.

Contrary to the phenomenon at play for conventional vehicles (lower mileage), the reduction in residential emissions through thermal renovation is counteracted by a 6% increase of housing surface per inhabitant (from 37.7m^2 per inhabitant to 40m^2 per inhabitant) between 2010 and 2035, in both scenarios.

Figure 2.B.5 – Renovated housing surfaces under F4 and NZE scenarios



Source: ThreeME, ADEME.

2.C Literature review of micro-macro modelling

Assessing the distributional impacts of climate policies can be done at several levels depending on the indicators that one wants to study, or the mechanisms one wants to include. Indeed, models can be subdivided according to their ability to account for the following policy impacts: demand-side or income-side effects; direct or indirect effects; aggregate or disaggregate effects. Three families of models allow each of these features to be considered accordingly (Ohlendorf et al., 2020). *Input-Output models* allow us to capture indirect effects. Changing a price, typically in the climate models, introducing a carbon price will disrupt the production and demand for inputs in all sectors that face it. Consequently, the prices of all other goods will be indirectly affected . Input-output models are based on eponymous matrices that detail the intermediate consumption of each sector: after introducing a disturbance (e.g. a carbon price offset) the output of each sector and the demand for that good are balanced between final consumption and intermediate inputs. New prices result from this equilibrium. However, in this type of model, final consumption is assumed to be exogenous, and demand-side effects are not considered. This is the case with microsimulation models, which very accurately model consumers' decisions and their responses to the new prices. Moreover, these models are disaggregated, usually on a broad household basis, representing the full heterogeneity of budgets and sometimes of choices (when demand is elastic). But households can also change their demand in the face of income changes. To model these we need a macro representation of the economy, for example via a computable general equilibrium (CGE) model that generalizes input-output models by integrating the "income part". However, most CGEs use only a single representative household.

Depending on the needs of the study, we may prefer a particular method. However, by neglecting one or more mechanisms, these choices inevitably introduce bias in the representation of distributional impacts. Accounting for general equilibrium effects, particularly source-side effects, mitigates the regressive effects of climate policies through two mechanisms. First, carbon-intensive goods are also capital-intensive. Hence, imposing a carbon tax reduces capital income relative to labour income. At the same time, the carbon tax raises the general price level, it translates in increased social transfers that benefit the poorest households to a greater extent. Second, the use of carbon tax revenues can largely reverse the regressivity of the tax (use-side), in particular through direct lump-sum transfer or cut of tax rates on labour or capital (see Rausch et al. (2011); Cronin et al. (2019); Fullerton et al. (2012)).

Neglecting these micro impacts could lead to an overestimating the macro impacts of the carbon tax Metcalf (2019). Nevertheless, it should be pointed out that Ohlendorf et al. (2020) finds little relationship between the presence of a CGE in the model toolbox and the progressivity of the outcome in its meta-analysis.

Conversely, Ohlendorf et al. (2020) finds a relationship between the progressivity of the outcome and the modelling of indirect effects, such as household demand adjustment. Household demand adjustment is a behavioural response (as opposed to static model) to price changes. The relative inelasticity of some energy goods (e.g. due to household dependence on transportation expenditures) can increase or decrease distributional impacts. In a microsimulation model, one can model lump-sum transfers (see Douenne (2020)) but not economy-wide policy. In particular, it is possible to evaluate the global efficiency of a given policy since microsimulation models are, by definition, partial equilibrium.

The trend in modelling the distributional impacts of mitigation policies is to combine or merge these different models to benefit from a quasi-exhaustive modelling of all the channels. Cockburn et al. (2014); Bourguignon (2001); Bourguignon et al. (2010) provide a comprehensive overview of the literature on linking macro and micro models. We will briefly present the different options.

The simplest and theoretically most satisfactory solution is to merge the micro and macro approaches, and to include as many representative households in a CGE model as are included in the microsimulation. This is the 'fully-integrated' approach. See for example the first models of Decaluwé et al. (1999) and Cogneau and Robilliard (2007), or focusing on the environment of Rausch et al. (2011) which integrates 15588 households into a static macro-model. Nevertheless, these models are complex because they require a perfect match between the macro-national accounts — and the survey data — mostly consumer expenditure survey — which is far from trivial[26]. Its numerical resolution is complex and generates many subproblems since solving the full simultaneous models with so many households is close to impossible. It also requires simplifying assumptions about households behaviour (Rausch et al. (2011) is a purely static model in which agents do not adjust their consumption to new prices. See also the iterative solution to the model, where a local equilibrium at the regional level to aggregate and solve for the full equilibrium.)

To overcome the limitations of a fully-integrated approach (called hard-link), sequential soft-link methods are often preferred. It describes a technique in which the macro and micro models are linked together and exchange variables at various steps in their work. The method is called 'top-down' when the CGE model provides policy-induced shocks (usually in the form of price changes and income returns) that are considered exogenous by the microsimulation model. The method is called 'bottom-up' when aggregate household responses to a shock are fed into the CGE model.

The top-down approach is most widely used, especially for development models, where the macro model may or may not include a behavioural response. The main issue then is that there is no feedback between the micro and macro levels. It may lead to potentially large discrepancies between the micro and macro results (see the study by Labandeira et al. (2009) comparing the macro results of a CGE model and those of a combination of top-down and bottom-up modelling, which shows significant differences). These differences are all the more important as the behaviour of agents in the microsimulation differs from that of the representative household in the CGE, especially for discrete regime switches[27] or in the case of fixed consumption — for instance, the subsistence level for energy consumption.

Therefore, it seems interesting to sequentially run a top-down (TD) approach and a bottom-up (BU) approach until the two models converge on a selected set of variables. This iterative method is more flexible than a fully integrated method and can model most of the desired feedback mechanisms. The next step is to decide whether the first model should be the macro or micro model (TD-BU vs BU-TD). If the CGE model is run first, it is easy to quantify the effects of feedback from the micro to the macro model, e.g. household adjustment behaviour or the decision to work in a particular sector via the reservation wage of individual households. Conversely, if the microsimulation precedes the macrosimulation, one can quantify the impact of general equilibrium effects on income dispersion, for example — savings and capital income are particularly sensitive to general equilibrium.

The main advantage of this iterative approach is that there is little constraint in the level of aggregation of each model : one can include as many sectors as needed in the CGE model or use the most detailed household expenditure surveys available, and aggregate/disaggregate the exchange variables as one goes along Savard (2003).

[26]For instance, capital income is regularly under-reported in surveys van Ruijven et al. (2015). See DREES note André et al. (2016) for a review of the main inconsistencies between the French expenditure survey and national accounts aggregates.

[27]From employed to unemployed households, or when technology are adopted.

With respect to our subject, the closest approaches are i)Buddelmeyer et al. (2012) which models a projection of the Australian economy to assess the effects of climate change mitigation using a top-down approach with reweighting for forecasting, and ii) Vandyck and Van Regemorter (2014) which uses the same technique in Belgium to assess the distributional effects of a fuel tax.

2.D Macro-micro consistency

The starting points of our numerical explorations are datasets of the French economy at a 2010 base year and for 3 projection horizons 2025, 2030 and 2035, for F4 and NZE scenarios. The source of these datasets are authoritative numerical simulations of the macro-economic model ThreeME maintained at the French environmental agency ADEME (see Appendix 2.B).

For each scenario and at each horizon, ThreeME results encompass the input-output table (IOT) of annual economic flows disaggregating the input structures and markets of 24 goods and services, among which 4 energy goods: coal products, oil products, gas (natural and biogas) and electricity. The input structures of branches account for the adaptation of firms to the price and non-price measures of scenarios, as well as for feedback effects from all factor markets.

The ThreeME model uses a Stone-Geary utility function for non-energy consumption: the residual consumption budget distributes across goods and services according to constant shares beyond the satisfaction of 'basic needs'. Our modelling framework replaces this specification with microsimulation. The economy-wide final consumption of energy goods by households follows exactly the dynamics derived from the microsimulation. These dynamics come from two mechanisms: the interplay of price and income elasticities and energy savings from renovations, new buildings and electric vehicles.

The main difficulty of linking macroeconomic and microeconomic models lies in the consistency of the two visions of the economy. Households tend to under-report income, especially capital income. Besides, consumption is noticeably lower in survey data than in national accounts (van Ruijven et al., 2015). Surveys do not include expenditures by other agents (public administrations, firms) that macroeconomic models attribute to households because of national accounting conventions, such as consumption of public education and health services or consumption of self-produced goods (André et al., 2016). Conversely, surveyed budgets detail transactions and transfers between households that the aggregation of households evens out in the consumption matrices of national accounts. We adapt our numerical method to these discrepancies. Aggregate consumption of BDF accounts for only 74% of national accounts. We calibrate the breakdown of the remaining 26% between non-energy consumptions to ensure consistency between ThreeME 2010 data and BDF aggregate consumption. We then assume that this gap is structural and that this breakdown is constant across time and scenarios. Energy shares are excluded from this deficit to allow the microsimulation dynamics of energy expenditures to pass on to IMACLIM-3ME without any transformation. The corrected non-energy shares forced in IMACLIM-3ME are the weighted averages of the micro-simulated shares and the shares in the national account residual. For instance, if microsimulation computes the aggregate budget share of food at 17.1%, while food consumption accounts for 14.1% of the 26% gap between BDF and national accounts, the corrected food share forced in IMACLIM-3ME is $(1 - 26\%) \times 17.1\% + 26\% \times 14.1\% = 16.34\%$.

2.E Microsimulation

Thermal renovations induce decreases in energy consumptions for heating, water heating and air conditioning purposes. Energy savings depend on the original and final EPD of dwellings. Each EPD transition at each year from 2010 to the forecast horizon is characterised by a coefficient of reduction of consumption, given by the ratio of the average heating — space and water — and air conditioning energy consumptions for the two EPD classes at the considered year in ThreeME forecasts.

To account for landlord-tenant dilemmas, we prioritise owner-occupiers and social housing for EPD shifts. Owner-occupiers are incentivised to renovate their dwellings as they bear the costs and reap the benefits of the investment. Social housing is to be renovated as part of the SNBC plan. We do not exclude tenants from the selection but only select them if the two former categories of occupiers do not allow covering the volume of renovations prescribed by ThreeME at any given year. In the latter case, we distribute the investment costs of tenants among landlords (households with income from housing rentals) and we increase each tenant's rent to exactly compensate annual investment costs in the dwelling. The selection procedure strikes an admittedly reasonable balance between the three household categories (Figure 2.E.6).

Each of these categories is classified according to the energy efficiency variants used for housing construction. The classification is dynamic and evolves in line with annual renovations. Any given household can carry out several successive renovations that gradually improve its EPD class, as long as the financing of these renovations does not violate the solvency condition: loan repayments and interest payments must not exceed 33% of annual income.

For households carrying out a renovation between 2010 and the forecast horizon, the budgetary consequences concern several items. First of all, energy bills are reduced by the energy savings achieved thanks to the jump in EDP class. These energy savings correspond to a savings factor that applies only to expenditure on heating, water heating and air conditioning, whether it be electricity, gas, fuel oil, wood or district heating. Social housing tenants are supposed to benefit from the energy savings without any increase in rent. Their renovation costs are duly allocated to public budgets in IMACLIM-3ME. In the case of owner-occupiers, the financial costs and the repayment of the loan used for the renovation are added to their budgets. In the case of tenants, the financial costs are borne by the owner-renter households (identified in the database by the presence of rental income), who pass them on in rent increases that exactly compensate for the renovation costs in the long run.

For renovations taking place at projection horizons, the renovation costs appear in household expenditure while the loan increases income by a similar amount. Induced energy savings only apply to half the concerned expenses to account for different timelines.

The same rule applies to new construction: we select households building new housing among those who already have 'housing purchase' expenditures in their budgets.

For households engaging into renovations, we assume strict equivalence between loan-financed and self-financed investment using savings. Indeed, we assume that paying back a loan is equivalent to building back savings (the latter inducing cuts of the returns on owned capital equivalent to loan interest payment). Loan-financed investments induce payback payments during a period of 25 years — without impact on any of the 14 consumption goods — and interests — which increase the consumptions of "other goods and services" (see section 3.3).

We allocate the net financial savings from renovation (EPD shift) on all consumption items except energy goods, using the estimated income elasticities (Chapter 1). Energy goods are left out of the allocation to acknowledge the fact that the energy saving coefficients derived from ThreeME forecasts are already net of rebound effects.

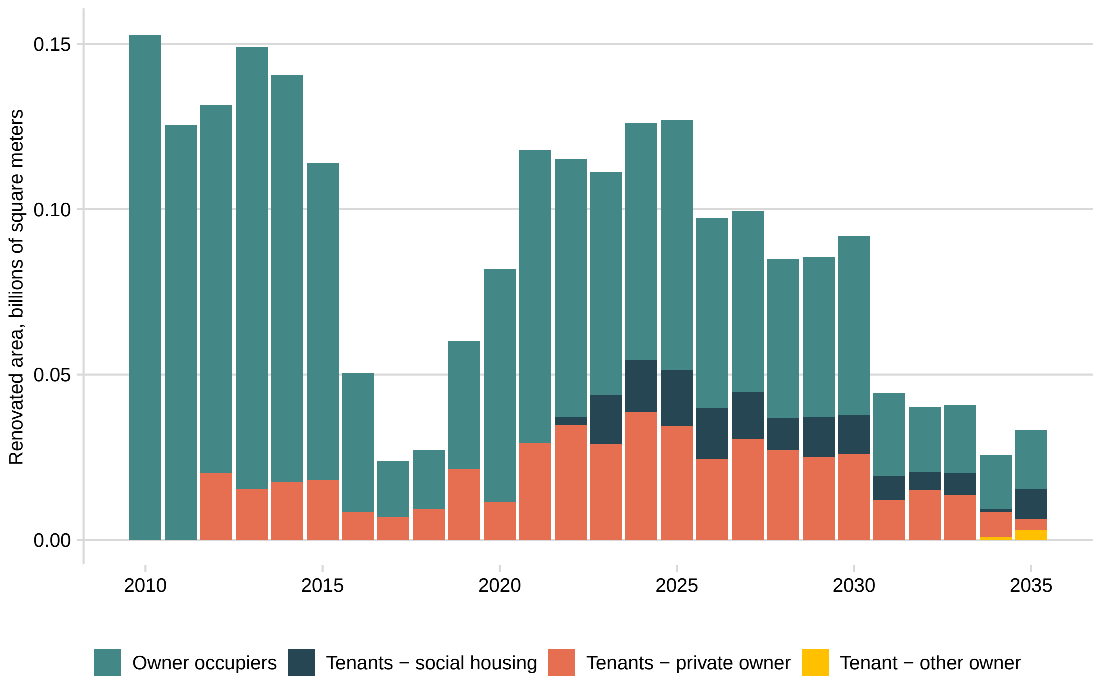
Similarly, we explicitly consider replacing conventional vehicles by electric vehicles (EVs) for each household of our database. For each year before the horizon of the simulation, households are ranked according to fuel consumption used for trips shorter than EV range without recharge (set at 300 km) in a way similar to thermal renovation.

The adoption of an electric vehicle leads to a decrease in fuel expenditure proportional to the share of private vehicle travel eligible for electromobility (that is the share of trips below the range of EV), and an increase in electrical energy expenditure. Electricity consumption associated with each EV is calculated by applying a cost per kilometre of electricity expenditure, deduced from ThreeME forecasts for each year, to the annual distance eligible for the EV. Only the fuel bill corresponding to the share of eligible trip is converted to electricity. Any remainder holds if the household owns more than one vehicle; it is allocated to other expenses along with net financial savings using income elasticities if the household only owns one single vehicle.

For selected EV buyers, the fuel consumption of eligible trips is switched to electric, using the average EV consumption per km from ThreeME. For households buying an EV before the forecast horizon, costs include investment costs for an average vehicle-loan repayment term of 6 years following purchase as in thermal renovation. We assume, following ADEME, that 13-year old EVs are systematically replaced by new ones.

We select EV buyers at forecast horizons (2025, 2030 or 2035) among households purchasing new vehicles in the original BDF survey and adjust their consumption budgets accordingly. This warrants that we do not distort too much the concerned budgets because they do already cover the purchase of a new vehicle. We increase the purchasing prices of vehicles by coefficients reflecting both the additional cost of an EV and the bonus/malus applying to the EV and conventional counterpart, as reported by ThreeME. For households buying an EV at the forecast horizon, only half of the vehicle fuel bill is actually transformed into electricity payment.

Figure 2.E.6 – Occupational status of renovated dwellings



Source: Authors' calculation. Results are for the NZE scenario with maximum energy savings and poverty-targeted rebates.

This modelling choice minimises spurious distributional impacts: we minimise disruption to household budgets, as large investments in durable goods were already present among households with the exception of renovations. We do not expect households building new houses and/or buying new cars to be very different sociologically in 2010 and 2035. By contrast, we do not impose conditions on households renovating before or at the horizon.

We select EV buyers on their absolute gasoline consumption, to bound the potential carbon emissions savings from electric vehicles within the three energy savings scenarios. Other selection criteria such as the age of cars, correlated with particulate matter emissions on top of CO_2 , would require unavailable data for a large share of households and would lower emissions reductions compared to the maximum energy savings variant.

We adopt absolute energy consumption as the criteria for thermal renovation to draw a parallel with vehicles. We have tested the alternative option of ranking households based on energy efficiency measured in kWh/m^2. It does not alter our results significantly (see Table 2.E.6).

Table 2.E.2 – Macro-economic aggregates, energy, carbon tax and emissions change in 2035 vs 2010 for NZE under maximum energy savings criteria for absolute (Abs.) and relative (Rel.) energy consumption

	Abs.	Rel.			Abs.	Rel.		
Macroeconomy				**Average Household carbon tax (€2019)**				
Real GDP	46.70%	46.40%	-0.3 pts	D1	349	352	0.90%	
Unemployment rate	+0.6 pts	+0.8 pts	+0.1 pts	D5	585	574	-1.90%	
Trade Balance / GDP	-0.7 pts	-0.7 pts	+0.1 pts	D9	766	771	0.70%	
Real Disposable Income	44.60%	44.30%	-0.3 pts	**Average per c.u. carbon tax (€2019)**				
Saving Rate	+2.9 pts	+3.3 pts	+0.3 pts	D1	272	274	0.70%	%
Real Consumption	43.00%	42.20%	-0.8 pts	D5	394	387	-1.80%	
Energy Consumption				D9	511	515	0.80%	
Coal & lignite	-61.50%	-61.50%	id.	**Average carbon tax share of income**				
Oil	-39.10%	-39.10%	+0.001 pts	D1	2.92%	2.93%	+0.01 pts	
Electricity	39.00%	39.00%	-0.001 pts	D5	1.55%	1.53%	-0.02 pts	
Gas & heat	-19.00%	-24.70%	-5.679 pts	D9	1.18%	1.19%	+0.01 pts	
CO_2 direct emissions	-53.30%	-53.90%	-0.005 pts					

Source: ThreeME, ADEME.

2.F Rebating options

The living-standard rebate has, by construction, neutral distributive impacts. Each household receives an amount proportional to their disposable income deflated by their number of consumption units (CU). The option is especially useful as a "neutral" counterfactual for assessing the impact of micro-simulation on IMACLIM-3ME results. Since the rebating options only affect macroeconomic aggregates by feedback, any change in the macroeconomy between rebating options would show the influence of the macro-micro linkage. Because the upper deciles spend lower proportions of their expenditures on energy, the living-standard rebate leads to a share of the carbon tax levied on lower deciles being returned to upper deciles. It is therefore proposed only as a counterpoint to politically realistic scenarios that envisage the opposite of such a transfer — the use of part of the payments from the upper deciles to compensate the lower deciles for the taxes they bear.

The per capita rebate is a lump-sum rebate that returns to all households an identical fraction per CU of the tax collected. Since energy expenditures increase with income, at least at certain levels of aggregation (notably the decile level), households in the lower deciles would receive on average more rebate than they pay taxes.

The poverty-targeted rebate is decreasing gradually, acknowledging that energy expenditures are poorly correlated with income at finer levels of disaggregation. The option therefore modulates the amount rebated per unit of consumption according to deciles, with lower amounts for the higher deciles. The precise rule is that the rebate to the first decile reflects the difference, calculated in 2010, between the average direct carbon emissions per CU for all households and the 95th percentile of the same emissions per CU for decile 1. The rebate is thus calibrated on the latest available statistics to fully compensate 95% of decile-1 households for their direct carbon tax payments calculated ex ante, i.e. without taking account of adaptation strategies. The difference in question, of 2.2, corresponds by construction to the ratio of this rebate and the sum rebated to decile-1 households in the above per capita rebate (they receive 2.2 times more). The rebates of deciles 2 to 9 are then calculated for each scenario and at each horizon under the assumption that each decile receives per CU an identical lower-than-one fraction of what the decile immediately lower receives per CU, under constraint that total rebates equal total tax payments. By hypothesis, decile 10 is not granted any rebate.

The geographical rebate reproduces the principle of the poverty-targeted rebate but according to the urban unit sizes (UUS) of households' places of residence. The rebate is calibrated to fully compensate 95% of the households residing in rural areas (UUS 0) from ex-ante direct tax payments. In 2010, the gap between the average direct carbon emissions per CU for all households and the 95th percentile of the same emissions for households in rural areas is 3.33. The fact that it is higher than the gap observed for deciles clearly shows that UUS are better indicators of the carbon tax burden than income deciles. However, the rule concentrates rebates on rural households (UUS 0) so much that the rebates accruing to households in UUS over 100,000 inhabitants are negligible compared to their tax payments. Moreover, the wide dispersion of fossil energy consumptions among rural households, for all the deciles of living standards, means that the amount rebated, given its size, massively overcompensates a large number of rural households.

2.G Ratio of carbon tax payment to income and expenditures

Total expenditures are a better proxy for lifetime income than current income (Friedman, 1957), as testifies the canonical example of the medical student. However, it is debatable whether they allow computing better indicators of the acceptability of reforms. To document that debate, we compute the expenditure shares of 2035 carbon tax payments in two F4 and NZE scenarios (Figure 2.G.7). The regressivity of carbon tax payments is diminished when measured in terms of expenditure shares rather than income shares, but persists from deciles 3 to 10.

2.H Regression of net carbon tax payment per household

2.I Time series from official low carbon strategy dataset

We provide in supplementary material all time-series from the official SNBC dataset that we used to calibrate the macroeconomic model IMACLIM-3ME and to constrain

Table 2.H.3 – Regression of net carbon tax payment per household in 2025

	Dependent variable: Net carbon tax payment	
	Living-standard rebate	
	(1)	(2)
Intercept	4,004.96***	4,711.30***
	(134.32)	(160.90)
log(income)	−471.49***	−573.33***
	(13.46)	(16.10)
Consumption units	562.65***	698.68***
	(16.64)	(19.76)
Rural (dummy)	204.97***	275.62***
	(22.95)	(27.07)
Small city (dummy)	132.13***	153.72***
	(20.87)	(24.48)
Age	−1.38***	1.40**
	(0.47)	(0.55)
Region	11.57***	7.04**
	(2.66)	(3.15)
Surface	1.06***	2.31***
	(0.18)	(0.22)
Electric Vehicle (EV)	0.12	−402.31***
	(84.91)	(80.54)
Rural×VE	−415.13***	−234.56*
	(106.37)	(142.59)
Small city×EV	−202.29*	−58.12
	(119.57)	(130.33)
Thermal Renovation (TR)	6.05	−273.42***
	(31.65)	(37.98)
Rural×TR	−22.88	1.59
	(45.73)	(55.72)
Small city×TR	−52.68	−22.61
	(44.58)	(55.13)
New Housing (NH)	43.44	−282.05***
	(42.02)	(43.47)
Rural×NH	89.11	−40.87
	(61.22)	(67.12)
Small city×NH	3.08	−23.43
	(62.55)	(70.86)
Observations	10,252	10,252
Adjusted R^2	0.16	0.19

*p<0.1; **p<0.05; ***p<0.01

Note: The baseline of the size of urban unit is Large cities of more than 100,000 inhabitants. Some households have been withdrawn due to negative or zero disposable income.

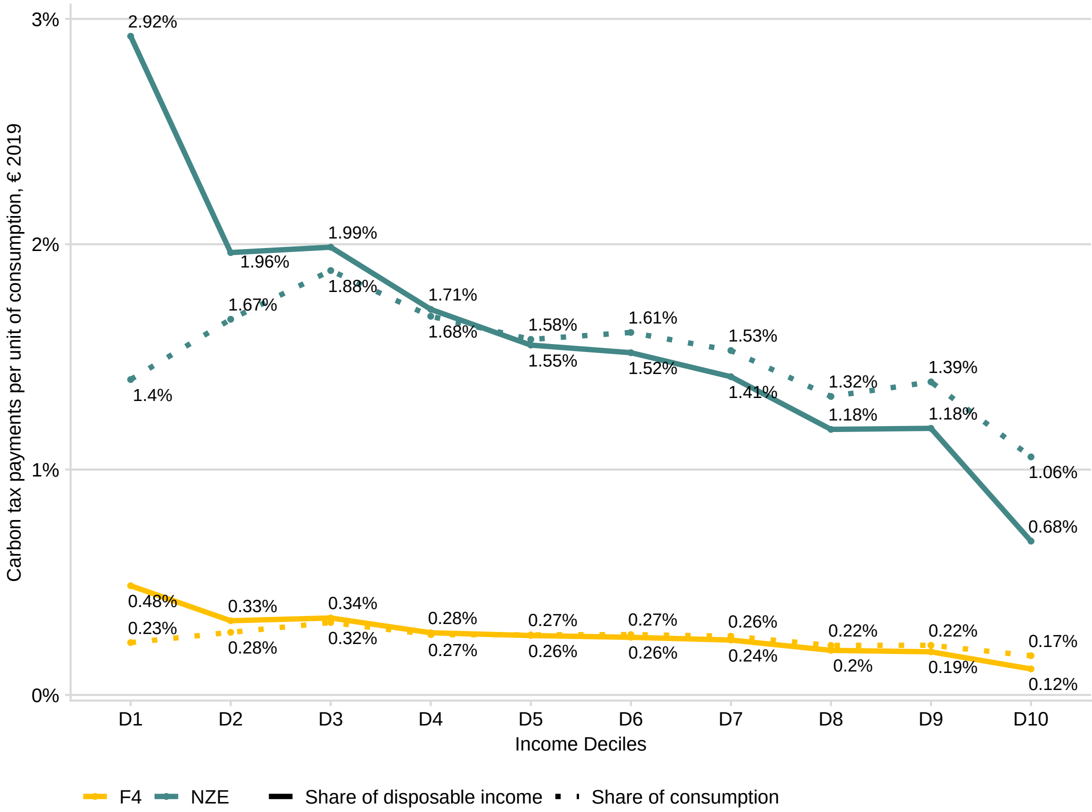
Table 2.H.4 – Regression of net carbon tax payment per household in 2035

	Dependent variable: Net carbon tax payment									
	No rebate		Poverty-targeted rebate		Per-capita rebate		Rural-targeted rebate			
	(Max)	(Min)	(Max)	(Min)	(Max)	(Min)	(Max)	(Min)		
Intercept	−1,399.56***	−3,353.19***	−9,873.65***	−14,300.76***	−854.57***	−1,709.27***	−312.59	−1,087.28***	7,176.31***	7,914.69***
	(217.80)	(299.52)	(277.08)	(393.96)	(229.76)	(203.26)	(250.60)	(219.45)	(251.59)	(343.32)
log(income)	174.55***	333.49***	1,042.48***	1,454.70***	123.81***	171.82***	153.16***	186.49***	−787.33***	−930.91***
	(20.98)	(28.85)	(26.63)	(37.81)	(22.09)	(19.56)	(24.16)	(21.19)	(24.16)	(32.94)
Consumption units	210.94***	397.30***	−1,094.27***	−1,285.28***	−408.18***	−299.11***	−421.58***	−314.27***	889.56***	1,288.78***
	(25.80)	(35.43)	(31.65)	(44.31)	(27.02)	(23.81)	(29.30)	(25.74)	(29.79)	(40.38)
Rural (dummy)	347.46***	568.34***	267.36***	464.22***	337.86***	330.40***	−2,998.29***	−2,692.08***	504.17***	780.34***
	(42.16)	(57.93)	(51.27)	(71.96)	(44.30)	(38.87)	(47.87)	(42.10)	(48.95)	(66.50)
Small city (dummy)	150.78***	253.74***	105.46**	180.99***	143.82***	144.69***	−503.29***	−450.22***	225.55***	338.25***
	(38.33)	(52.97)	(46.57)	(65.76)	(40.28)	(35.55)	(43.47)	(38.66)	(44.52)	(60.76)
Age	−4.01***	−4.61***	−6.28***	−7.85***	−4.27***	−2.39***	−1.27	0.31	−2.25***	−2.15*
	(0.74)	(1.00)	(0.89)	(1.24)	(0.77)	(0.67)	(0.83)	(0.73)	(0.85)	(1.15)
Region	8.03*	10.65*	3.83	4.75	5.97	1.65	4.33	0.11	16.06***	19.88***
	(4.10)	(5.64)	(5.00)	(6.99)	(4.28)	(3.78)	(4.64)	(4.09)	(4.75)	(6.45)
Surface	3.51***	7.23***	5.35***	9.91***	3.81***	6.07***	3.27***	5.61***	1.70***	4.97***
	(0.27)	(0.37)	(0.33)	(0.46)	(0.28)	(0.25)	(0.31)	(0.27)	(0.31)	(0.43)
Electric Vehicle (EV)	−181.90***	−764.75***	−114.30	−875.19***	−180.81***	−472.73***	11.17	−393.16***	−188.56***	−787.26***
	(57.75)	(71.29)	(70.39)	(88.33)	(60.31)	(47.62)	(66.23)	(51.32)	(66.83)	(81.36)
Rural×VE	−406.82***	−584.85***	−420.51***	−573.50***	−406.17***	−398.64***	−952.21***	−425.21***	−422.92***	−590.82***
	(78.81)	(117.06)	(96.06)	(145.21)	(82.19)	(78.57)	(89.22)	(85.10)	(91.31)	(133.79)
Small city×EV	−260.84***	−153.33	−251.76**	−151.18	−255.39***	−110.77	−508.26***	−165.49**	−267.84***	−120.48
	(82.15)	(109.47)	(100.30)	(135.22)	(85.87)	(73.34)	(93.84)	(78.88)	(95.36)	(124.96)
Thermal Renovation (TR)	−262.76***	−242.17***	−337.22***	−366.88***	−269.04***	−266.43***	−333.12***	−372.90***	−287.67***	−280.24***
	(38.79)	(53.91)	(47.27)	(66.79)	(40.30)	(36.01)	(43.69)	(38.93)	(45.01)	(61.56)
Rural×TR	−154.96**	−118.53	−128.03*	−48.61	−158.39**	−88.61	60.74	133.43**	−133.43*	−95.80
	(62.51)	(88.41)	(76.21)	(109.53)	(65.13)	(59.25)	(70.79)	(63.73)	(72.46)	(100.99)
Small city×TR	−39.98	−94.38	−29.67	−64.15	−31.08	−53.44	−14.54	−3.85	10.02	−30.66
	(59.72)	(82.44)	(72.72)	(102.06)	(62.07)	(55.18)	(67.28)	(59.61)	(69.18)	(94.15)
New Housing (NH)	13.32	−331.35***	56.98	−294.79***	10.03	−365.50***	66.00	−444.92***	40.73	−344.25***
	(52.21)	(67.29)	(63.68)	(83.47)	(54.55)	(45.20)	(59.59)	(48.64)	(60.35)	(77.12)
Rural×NH	−79.61	−177.64*	−126.73	−272.67**	−76.17	−141.56**	−129.42	−7.85	−86.73	−222.42*
	(78.36)	(101.07)	(95.50)	(125.32)	(81.86)	(67.75)	(88.59)	(73.44)	(90.75)	(115.73)
Small city×NH	−96.06	−149.74	−127.92	−145.80	−89.64	−111.46	−148.35*	−203.86***	−68.41	−85.83
	(77.02)	(104.72)	(93.98)	(129.85)	(80.60)	(70.27)	(87.85)	(75.60)	(89.23)	(119.86)
Observations	10,251	10,251	10,260	10,263	10,257	10,256	10,254	10,254	10,252	10,252
Adjusted R^2	0.11	0.21	0.23	0.26	0.07	0.16	0.53	0.51	0.16	0.19

*p<0.1; **p<0.05; ***p<0.01

Note: The baseline of the size of urban unit is Large cities of more than 100,000 inhabitants. Some households have been withdrawn due to negative or zero disposable income.

Figure 2.G.7 – Income versus expenditure shares of carbon tax payments in 2035



Source: Authors' calculations. Scenario F4 and NZE, under maximum energy savings without any rebate.

the microsimulation from base year 2010 to 2035.

CHAPTER 3

Disentangling the directions of technical change: a new growth accounting method

Joint work with Mehdi Senouci (Université Paris-Saclay)

> Combien est-ce que j'en ai fait les dernières dix minutes ? Je ne vais pas assez vite. Je force encore, peu à peu, la monotonie de la tâche m'entraîne à rêver. Pendant quelques instants, je pense à bien des choses. Réveil brusque : combien est-ce que j'en fais ? Ça ne doit pas être assez. Ne pas rêver. Forcer encore. Si seulement je savais combien il faut en faire !
>
> Simone Weil, *Journal d'Usine*

Abstract

Current growth theories do not allow for the study of the bias of technical change and the evolution of factor shares — at aggregate nor sectoral level — without strong assumptions on the elasticity of substitution between capital and labour. We present a growth accounting framework that disentangles the different factor-saving directions of technical change and factor substitution. We build the framework for two primary factors, capital and labour. We represent technical change as the shift of a Leontief production function to a new function which is the convex hull of two shifts of this Leontief production function: one purely labour-saving, the other purely capital-saving. We apply this framework to industry-level data to answer the following questions: What has been the bias of technical change? Does an increase in the price of one factor spurs specific factor-saving innovation? Can we forecast the evolution of factor shares? We find that most industries are capital-biased but with a growing trend of labour-saving technical change. In some industries, we find significant evidence of labour-saving technical change induced by the cost of labour. The framework is validated by better forecasting the evolution of the factors shares than CES, Cobb-Douglas and Leontief functions.

Preamble In this chapter, we develop a conceptual framework to study technical change that is more general than the scope of this dissertation. The direction of technical change and the factor share are of prime importance for distributional impacts as they influence the distribution of income, that is the distribution of cost between labour and capital.

We describe technical change with only two inputs — capital and labour. We assess the bias of technical change, that is, eventually on wages, employment and capital income; and to what extent technical change is price-induced. It is a first step limited to capital and labour before studying multi-dimensioned technical change. The objective is to apply this framework to energy and material: it would allow us to study whether carbon pricing spurs energy-saving technical, and the consequences on labour and capital incomes — source-side distributional impacts to complement the analysis of Chapter 2. We present preliminary results of this framework extension to 5 inputs, including energy, in the final section of this chapter.

1 Introduction

Technical change is an increase in the productivity of the factors of production. More often than not, it is not neutral and benefits some inputs more than others. That is, some innovations may increase relatively more the marginal productivity of one factor. This bias of technical change has important impacts on the economy, especially on income distribution and CO_{2eq} emissions. Energy-saving innovations would decrease the volume of emissions or pollution. Likewise, labour-saving or capital-biased innovations — new and more efficient machines, for instance — reduce the relative demand for labour and limit the growth in employment and in wages compared to capital income.

Policymakers might want to stimulate technical change — and economic growth — in a specific direction to limit inequalities or emissions. One major hypothesis is from *The Theory of Wages*, by Hicks (1932), stating that innovation saves on the factor becoming relatively more expensive. Taxation of some factors, among other tools, might then increase innovation.[1] However, a rise in factor prices may yield technical change,

[1]The direction and magnitude of technical change is the result of the combined influence of many factors of which price is only one. Among others, we can also cite stringent regulations (Porter, 1996), the volume of human capital (Mankiw et al., 1992), R&D investments (Acemoglu, 2002), competition (Aghion et al., 2005), input scarcity (Habakkuk, 1962; Acemoglu, 2010), and the structure of the firm (Aghion et al., 2013).

but also result in mere substitution of factors that have become more expensive, without any innovation.

In this chapter, we develop a growth accounting framework that allows us to disentangle the different directions of technical change from each other and factor substitution. We use this framework to answer three questions: What has been the bias of technical change? Does an increase in the price of one factor spurs specific factor-saving innovation? Can we forecast the evolution of factor shares? We use KLEMS databases to study the factor-saving and factor-using components of technical change at the industry level in the U.S. and Europe. We use the intensities of biased technical change to test Hicks's hypothesis of price-induced technical change, with 2 inputs — capital and labour —- and 5 inputs, including energy. We test the ability of the framework to forecast the evolution of the labour share of various U.S. industries.

We build our framework on a Leontief production function with two inputs, capital and labour. Any technical change can be represented as a shift of the production function to a new one. We disaggregate this shift into two distinct shifts of the production function: one is purely labour-saving, the other is purely capital-saving. The new production function, after technical change, is the convex hull[2] of these two local functions. This new global production function is not Leontief but piecewise linear, which means that substitution between inputs can take place on the revealed convex hull. We can thus distinguish between the labour-saving and capital-saving components, and the substitution between the two factors. The framework is flexible and can operate on an arbitrary number of inputs. We apply this framework to KLEMS database, disaggregating inputs — capital, labour, energy, material and service — and output per industry in Europe and the U.S. (Stehrer, 2021; Van Ark and Jäger, 2017; Timmer et al., 2007).

We find that all European and U.S. industries exhibit both capital-saving and labour-saving technical change. However, the aggregate technical change is labour-biased, that is, the capital-saving technical change component is larger than the labour-saving one. We show a clear trend towards more and more labour-saving technical change, which might lead to an aggregate labour bias. Some industries are exceptions and show capital bias: agriculture, non-sustainable manufacturing, and finance. We find that in Europe, the substitution between factors strongly complements technical change with a capital deepening of some sectors. We highlight great heterogeneity between industries.

Our results are in line with most of the literature studying the technical change bias at the industry level. We can link trend breaks in our estimate of the technical change bias to specific technologies that have disrupted multiple industries. It shows that our framework can describe technical change in a great number of contexts. We further validate the relevance of our framework by comparing its predictive power on the evolution of the labour share. We find that our framework performs better than CES,

[2] Or convex envelop.

Cobb-Douglas and Leontief production functions to forecast the labour share at 6 years, and even better on longer periods.

We find evidence confirming Hicks's hypothesis of price-induced innovation. We test for different specifications of Hicks's hypothesis on multiple datasets. We find mixed evidence in some cases, but two clear results stand out. We find strong evidence that an increase in the cost of labour causes a capital bias of technical change (the technical change is relatively more labour-saving than capital-saving). We also find an increase in the capital-using technical change intensity following an increase in the cost of labour. Note that our results hold for a number of sectors but that many yield insignificant results.

This chapter contributes to two strands of literature. The first is the representation of technical change in production functions. The second is the estimation of the bias of technical change at the country and industry levels.

We contribute to the literature on aggregate production with a new method to represent technical change using the factors shares and not the elasticity of substitution. Although our framework is not micro-founded, we contribute a simple production function to represent the bias of technical change and the dynamics of the labour share. The first wave of technological change studies of the 1960s (Solow, 1957; Kennedy, 1964; Samuelson, 1965; Drandakis and Phelps, 1966), happened at a time when the labour share was stable in developed economies: this is the fifth of Kaldor's six stylised facts (Kaldor, 1961). Thus, technical change should simply accommodate capital accumulation by increasing labour productivity. To ensure a stable labour share, technical change must be purely labour-augmenting in the long run (Uzawa, 1961). But since the 1980s, this share has been declining (Bentolila and Saint-Paul, 2003; Karabarbounis and Neiman, 2014). Representing technical change in the production function has become necessary to describe this decline as it is believed to be one of the main drivers of the fall of the labour share.[3]

To recognise the bias of technical change, one must distinguish technical change from mere substitution between factors. The Cobb-Douglas function, which assumes fixed factor shares, is inadequate to represent these phenomena (Solow, 1956). The much more flexible Constant Elasticity of Substitution (CES) function (Arrow et al., 1961) has been widely adopted in its place. As the name suggests, the key parameter in the estimation of the CES function is the elasticity of substitution: between capital and labour, or between low-skilled and high-skilled workers, etc. The value of the elasticity of substitution is a major assumption in theoretical models describing micro-founded mechanisms of innovation and technology adoption. Acemoglu (2002) explains the decline of the labour share by capital-biased technical change. This result relies on labour and capital being gross complements (elasticity of substitution lower than one). With an elasticity greater

[3]Blanchard et al. (1997) proposes other explanations in addition to the technical change bias: the diminishing bargaining power of unions and thus of workers, the trend towards off-shoring, the increase of the markup, the decoupling of wages and productivity, automation, the rise of the digital economy, etc. Autor et al. (2020, 2017) examine the role of superstar firms in the fall of the labour share. For a full review see Cette et al. (2020); Brugger and Gehrke (2017); Blanchard et al. (1997).

than one, technical change would have had to be labour-biased to explain this movement. Likewise, the results on the direction of technical change from the task models — which finely represent the decision to automate specific tasks and the employment of more or less skilled workers (Acemoglu and Restrepo, 2020, 2018; Acemoglu and Autor, 2011) — relies on the hypothesis that the elasticity of substitution between low and high skills is greater than one.

Yet, empirical estimates fail to ascertain the value of the capital-labour elasticity of substitution: higher than unity (Karabarbounis and Neiman, 2014; Piketty and Zucman, 2014; de La Grandville, 2016; Berthold et al., 2002) or lower than unity (Antras, 2004; Klump et al., 2007). Estimates depend on the methods but also on how the bias of the directed technical change is integrated into the estimation. Diamond's theorem (Diamond et al., 1978) states that if one wants to estimate the elasticity of substitution and take into account the bias of the technical change, one must constrain the functional form of the production function. Caballero et al. (1995) finds elasticities of substitution between 0.1 and 2 for manufacturing sectors. León-Ledesma et al. (2010) concludes that direct estimation remains problematic. Raval (2019) estimates that capital-labour substitution elasticities in the U.S. are less than unity for the majority of U.S. industries. A reason why estimating elasticities of substitution is difficult, is that it is likely that elasticities change over time to reflect part of the technical change (Brown and De Cani, 1963; Koesler and Schymura, 2015; León-Ledesma and Satchi, 2019) and encapsulate many different effects.

The first contribution of our framework is to present a simple representation of technical change and substitution in a production function that does not require any assumption about the value of the elasticity of substitution. We use Leontief production function and constrain the shape of the global production function using the factor shares. We impose the slope of the production function when calibrating the model to derive the expression of the intensities of factor-saving technical change for each input. This is another way to approach Diamond's impossibility theorem (Diamond et al., 1978). However, a main limitation of our framework is that this representation of technical change is not micro-founded. We show in the section 6 that these hypotheses perform as well as estimating the elasticity of substitution and using a CES function to forecast the dynamics of the labour share.

We also contribute to the literature estimating the bias of technical change on country- or industry-level data. This chapter is most related to Jin and Jorgenson (2010), Doraszelski and Jaumandreu (2018), Herrendorf et al. (2015), and Young (2013) which estimate aggregate production functions and decompose growth into substitution and biased technical change.[4] Jin and Jorgenson (2010) uses KLEMS data, and splits between the two types of technical change — the sum of autonomous and price-induced

[4]We can also relate to some other papers. Dissou et al. (2015) does not succeed in highlighting a trend in the bias of technical change on Canadian sectors, Young (2013) shows that the U.S. industries are predominantly net labour-saving (capital biased), Villacorta (2018) does not find any conclusive bias. Note that the analysis is country-level rather than industry-level. Armanville and Funk (2003) empirically finds a relationship between changes in factor-productivity and changes in prices.

technical change — and factor substitution. The model is based on a translog model like the one proposed by Binswanger (1974). It finds that autonomous technical change dominates both induced technical change and substitution. Counter-intuitively, the correlation between prices and induced technical change is negative: high prices lead to input-using technical change, but the positive trend of autonomous technical change dominates. Doraszelski and Jaumandreu (2018) decomposes productivity growth into labour-augmenting technical change and Hicks neutral technical change. It shows that both are of similar magnitude, but that labour-augmenting technical change is the main source of the decline in the labour share in Spain in the 90s-00s. Using a Markov process, it integrates R&D into the evolution of productivity (Doraszelski and Jaumandreu, 2013), and shows that it plays a primary role in technical change. Herrendorf et al. (2015) estimates a CES production function by allowing labour- and capital-augmenting technical change. It shows that there is a fast labour-augmenting technical change in agriculture, but little technical change at all in services. Overall, it finds little capital-augmenting technical change. It concludes that a Cobb-Douglas function predicts structural change in the U.S. well enough.

The second contribution of our framework is then to offer a flexible tool to estimate the bias of technical change and substitution on as many inputs as needed and on all sectors. We can estimate the bias of technical change at any scale, from country to firm level. We provide a description of the bias of technical change in multiple sectors and countries. We use these estimates to test the causal relationship between price variations and the bias of technical change, and we find evidence of partial price-induced technical change in a number of industries.

The remainder of this chapter is organised as follows. In section 2, we introduce the theoretical and the growth accounting framework for two inputs — capital and labour. Section 3 describes the database we use and the calibration of the framework. In section 4, we describe the trends in the bias of technical change in U.S. and European industries, and the complementarity of factor substitution and technical change. In section 5, we present our test of Hicks' hypothesis and its results. In section 6, we forecast the evolution of the labour share and compare the results with a basket of classical production functions. Section 7 extends the framework to 5 inputs, and tests for price-induced energy-saving technical change. Section 8 concludes.

2 Framework

This chapter proposes a framework for describing and accounting for technical change and growth. It is based on two main assumptions: i) technical change can be disaggregated into two elementary directions, one purely labour-saving and the other purely capital-saving; and ii) production functions are Leontief.

Suppose a production function using capital K and labour L to produce output Y. Substituting labour for capital, or vice versa, means moving along this production function. However, it is impossible to reach a situation where the same quantity of output is produced using the same capital but less labour. This is what technical change does: labour-saving technical change makes it possible to reduce the use of labour to produce the same output, and capital-saving technical change means that less capital is needed for the same amount of output with the same amount of labour.

Technical change is a shift — a distortion — of the production function in order to reach new production possibilities which were previously unattainable. The expression of the production function changes accordingly, and it can be considered a new production function.

The shift of the production function is a priori indeterminate. In this chapter, we propose a framework allowing us to describe any shift of a Leontief production function using two independent elementary shifts of this function. The first of these shifts is purely labour-saving, i.e. a deformation of the production function where it uses less labour to produce the same thing. The second shift is purely capital-saving. The combination of the two shifts within their convex hull makes it possible to describe any movement in the production function.

We use Leontief production functions. The particularity of these functions — in addition to their simple form which is particularly appreciated to simplify the calculations — is that they do not allow for input substitution. Our identifying assumption is that any change in production is therefore technical change. Note that the convex hull of two Leontief functions is not a Leontief, thus allowing eventually for substitution.

In the following subsections, we present some theoretical results to construct a global production function by allocating inputs to two local Leontief production functions (section 2.1). Then we use these results to describe the technical change between two successive states of production in terms of their outputs, inputs and factor shares (section 2.4). Finally, we present a growth accounting framework that distinguishes technical change from capital deepening in the dynamics of value-added per worker (section 2.5).

2.1 Mathematical background

2.2 Leontief production functions

We define a Leontief production function, in intensive and extensive forms (Figure 3.1).

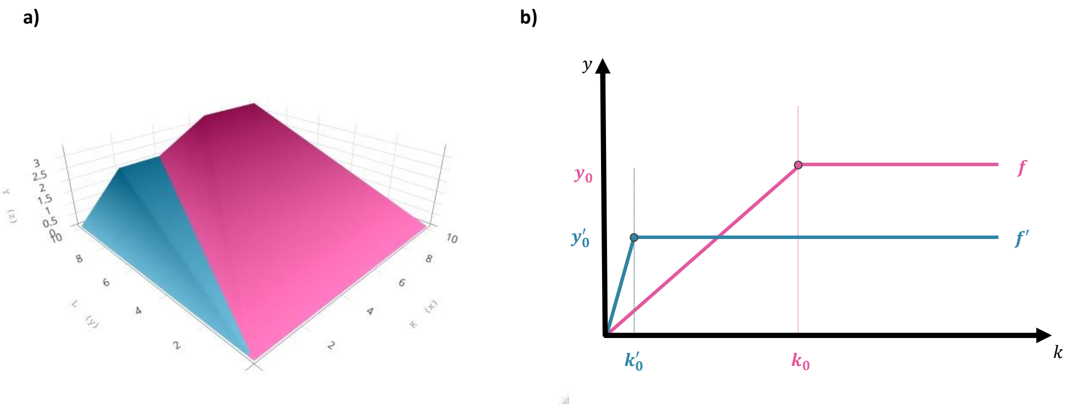
Definition 1. A Leontief function is a function F such as:

$$\begin{array}{lll} F & : \mathbb{R}_+ \times \mathbb{R}_+ & \rightarrow \mathbb{R}_+ \\ & (K, L) & \mapsto F(K, L) = Y = \min(A_K K, A_L L). \end{array} \tag{3.1}$$

It can be expressed relative to a certain point $Y_0 = F(K_0, L_0)$

$$\begin{array}{lll} F: & \mathbb{R}_+ \times \mathbb{R}_+ & \rightarrow \mathbb{R}_+ \\ & (K, L) & \mapsto F(K, L) = Y = Y_0 \cdot \min\left(\frac{K}{K_0}, \frac{L}{L_0}\right) \end{array} \tag{3.2}$$

Figure 3.1 – Two Leontief prodution functions in extensive (a) and intensive (b) forms



The intensive Leontief production function, in a framework (y, k), is then:

$$\begin{aligned} f: \quad \mathbb{R}_+ \quad &\rightarrow \quad \mathbb{R}_+ \\ k \quad &\mapsto \quad y = y_0 \cdot \min\left(\frac{k}{k_0}, 1\right) \end{aligned}, \tag{3.3}$$

with $y = Y/L$ the output per worker ($y_0 = Y_0/L_0$), and $k = K/L$ the capital per worker ($k_0 = K_0/L_0$).

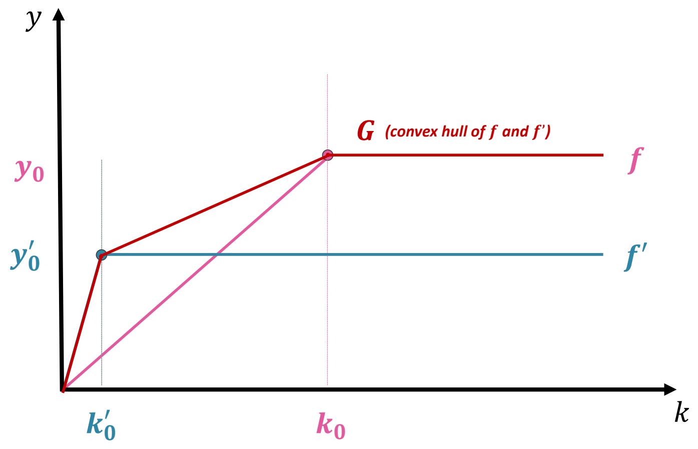
Definition 2 (Characteristic ratio)**.** A Leontief function has a *characteristic ratio* K_0/L_0 for which it is optimal, meaning the function is used efficiently. Any increase in one of the factor would not increase the output. In an intensive framework, the *characteristic point* is the output per worker y_0 than the function can reach in the capital per worker k_0.

2.3 Combining two production functions

Definition 3 (Dominance)**.** F and F' are two Leontief production function, F *dominates* F', if $\forall (x, y) \in \mathbb{R}_+^2, F(x, y) \geq F'(x, y)$.

Remark. If two functions are equal, then the first one dominates the second and reciprocally.

Figure 3.2 – Two Leontiefs production functions f and f' and their convex hull G



A global production function can be constructed by combining (summing) two local production functions. The global production function is no longer a Leontief production function but maximises the production at any capital per worker k.

Proposition 1. *Let us have two Leontief production functions without one dominating the other. We can build a global production function which is the convex hull of the two local production functions. Depending on the ratio of capital to labour, inputs are allocated either to one function or to both.*

We need two lemmas to demonstrate Proposition 1 (Lemmas' proofs are available in appendix 3.A). The first lemma states that two Leontief functions will intersect unless one dominates the other. The second then states that if they intersect, then their convex envelope creates a third production function G that maximises output production.[5]

Lemma 1 If two Leontief production functions exist without one dominating the other on $\mathbb{R}_+$, then these two functions intersect and this intersection is a line including the origin.

Lemma 2 From two local Leontief production functions F and F' that do not dominate each other, we can construct a global function G by efficiently allocating inputs $(\bar{K}, \bar{L})$ to these two functions:

$$G\left(\bar{K}, \bar{L}\right) = \left[\begin{array}{cc} \max_{(K,K',L,L')} & F(K,L) + F'(K',L') \\ \text{with:} & \begin{cases} K + K' \leq \bar{K} \\ L + L' \leq \bar{L} \end{cases} \end{array} \right]. \quad (3.4)$$

[5]If they don't dominate themselves, the convex hull is not a Leontief, there is a domain in which there is a possibility of substitution between factors.

1. Function G is the convex hull of F and F', it can be expressed as follows:

$$G = \begin{cases} F'(\bar{K}, \bar{L}) & \text{if } \bar{k} < k'_0 \\ F'\left(\bar{L}\frac{k_0(k_0-\bar{k})}{k_0-k'_0}, \bar{L}\frac{k_0-\bar{k}}{k_0-k'_0}\right) + F\left(\bar{L}\frac{k_0(\bar{k}-k'_0)}{k_0-k'_0}, \bar{L}\frac{\bar{k}-k'_0}{k_0-k'_0}\right) & \text{if } k'_0 < \bar{k} < k_0 \\ F(\bar{K}, \bar{L}) & \text{if } k_0 < \bar{k} \end{cases} . \quad (3.5)$$

   with $\bar{k} = \frac{\bar{K}}{\bar{L}}$, $k_0 = \frac{K_0}{L_0}$, $k'_0 = \frac{K'_0}{L'_0}$.

2. The allocation of inputs to production functions F and F' that is reflected by equation (3.5) is the competitive market allocation.

Proof of Proposition 1

Proof. We want to build a global production function using the two local production functions at our disposal. From Lemma 1, no single function performs better in every point. We can build a global production function G defined as in equation (3.5), which maximises output by allocating inputs to one or both of the local production functions (see Lemma 2). This function is the convex hull of the two functions: any function whose output is higher than G in any point is not within the minimal convex set containing all output produced by allocating input to the local production functions, since G is the maximum of this set. Reciprocally, a function inferior to G in any point would not contain the allocation corresponding to G. □

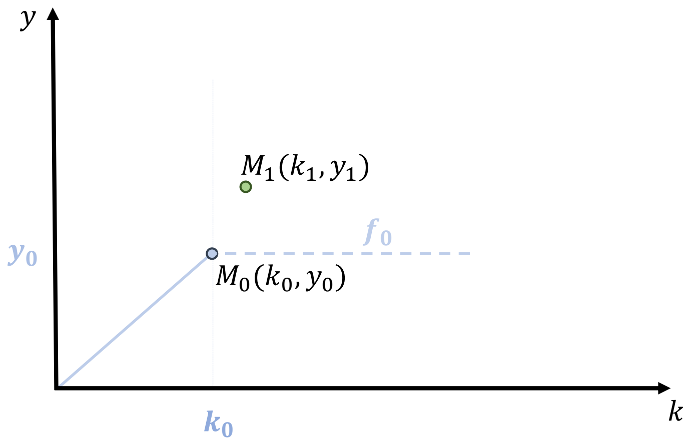
2.4 Application to technical change

Starting from a Leontief production function, the technical change is decomposed into two directions purely labour-saving and capital-saving. These two directions are represented by two local Leontief production functions obtained by shifting the first Leontief production function. We then obtain the global production function by allocating inputs to one or two of these functions to reach the convex hull of two functions. From the proposition 1 we know how to build these functions.
We present the construction of the framework in 3 steps.

Step 1: Starting situation

Let us consider some point in time $t = 0$ and a Leontief production function F_0 such as $F_0(K, L) = Y_0 \min(K/K_0, L/L_0)$. Output Y_0 is produced using K_0 capital and L_0 labour inputs. In Figure 3.3, the production is represented by the point M_0 and f_0, the intensive form of the production function F_0.
Factors shares of capital and labour are expressed as: α_{K_0} and α_{L_0} defined as $\alpha_K = rK/Y$ with r the real price of capital, likewise $\alpha_L = wL/Y$ with w the real wages. We assume perfect competition, all factors are paid their marginal products.

Figure 3.3 – Step 1 — Starting situation: two points and a production function



Production at time $t = 1$ is Y_1, with inputs K_1 and L_1, and production, it can be summarised in a point $M_1 = (K_1, L_1, Y_1)$ corresponding to factor shares α_{K_1} and α_{L_1} (Figure 3.3).
If as in figure 3.3 point M_1 is not on the f_0 then it means that it is not possible to produce Y_1 by using F_0 with (K_1, L_1).
That means that *technical change* happened between time $t = 0$ and time $t = 1$.

Step 2: Labour-saving and Capital-saving production functions

The objective of the framework is to describe the transition from M_0 to point M_1 and their respective factor shares by shifting the production F_0 into a capital-saving production function: $F_{\lambda_K}(K, L)$ and a labour-saving production function $F_{\lambda_L}(K, L)$ (f_{λ_K} and f_{λ_L} in intensive form (Figure 3.4).

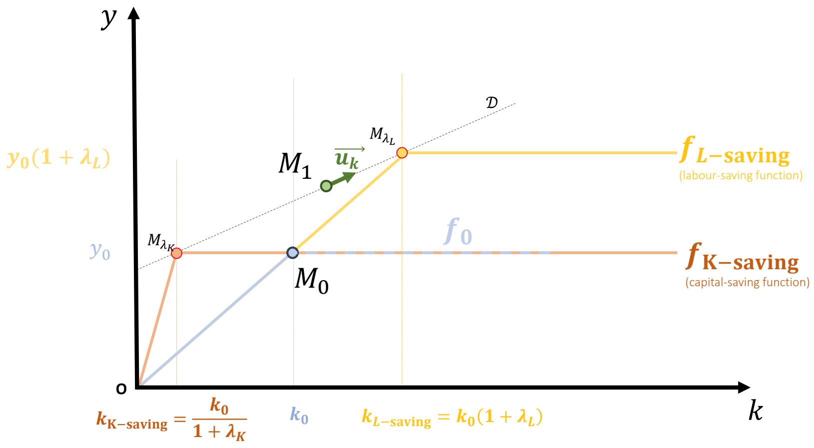
Factor-saving functions The two factor-saving functions are expressed as follows:

$$F_{\lambda_K}(K, L) = Y_0 \min\left(\frac{K}{\frac{K_0}{1+\lambda_K}}, \frac{L}{L_0}\right) \tag{3.6}$$

and

$$F_{\lambda_L}(K, L) = Y_0 \min\left(\frac{K}{K_0}, \frac{L}{\frac{L_0}{1+\lambda_L}}\right). \tag{3.7}$$

Figure 3.4 – Step 2 — Labour-saving and Capital-saving shift of the f_0 production function



Note: Other constructions with factor-using technical change (either $\lambda_L < 0$ and/or $\lambda_K < 0$ are shown in appendix 3.B

f_{λ_k} and f_{λ_k} are the intensive functions associated with $F_{\lambda_K}(K, L)$ and $F_{\lambda_L}(K, L)$, their characteristic points are $M_{\lambda_K} = \left(\frac{k_0}{1+\lambda_K}, y_0\right)$ and $M_{\lambda_L} = (k_0(1+\lambda_L), Y_0(1+\lambda_L))$.[6]

We use the definition of factor-saving technical change from Hicks (Hicks, 1932) "*A capital-using and labour-saving innovation is a change in the technological parameters such that, holding the factor prices constant, the optimal capital labour ratio is increased.*" (Hicks, 1932).

The function $F_{\lambda_K}(K, L)$ (3.6) is capital-saving for any $\lambda_K > 0$. Its characteristic ratio is $\frac{K_0}{L_0}\frac{1}{1+\lambda_K}$ against K_0/L_0 for F_0. The decrease of this characteristic ratio means, according to Hicks' definition, that the technical change from one function to the other is capital-saving.

Similarly, the function $F_{\lambda_L}(K, L)$ (3.7) is labour-saving with respect to F_0 for any $\lambda_L > 0$ since its characteristic capital-labour ratio is $\frac{K_0}{L_0} \cdot (1+\lambda_L) > \frac{K_0}{L_0}$. It is similar to factor-augmenting technical change.

Identifying λ_L and λ_K We identify the parameters λ_L, λ_K with two conditions:

1. We want a global production function F_1 that can produce Y_1 with K_1 and L_1. Hence M_1 belongs to the convex hull of $F_{\lambda_K}(K, L)$ and $F_{\lambda_L}(K, L)$. We assume

[6] For the sake of simplicity, the same notations refer to the equivalent points in the 3-dimensional extensive space

that F_1 is distinct from the two factor-saving functions.[7] Hence $M_1 \in \mathscr{H}$, with $\mathscr{H}$ the plan between the two factor-saving functions that contains M_{λ_L} and M_{λ_K} as per (3.5). In intensive framework (2D), this $\mathscr{H}$ is represented by the the line $\mathscr{D}$ (Figure 3.4). Hence, the vectors $\overrightarrow{OM_{\lambda_K}}$, $\overrightarrow{OM_{\lambda_L}}$ and $\overrightarrow{OM_1}$ are included in $\mathscr{H}$ with O the origin.[8]

2. The framework accounts for factor shares. We assume perfect markets, which translates into capital cost r and wage w equating F_1 first derivatives at M_1:

$$\frac{\partial F_1}{\partial K} = r_1 \text{ and } \frac{\partial F_1}{\partial L} = w_1. \tag{3.8}$$

   This means that at M_1 the vectors $\overrightarrow{u_K} = (1, 0, r)$ and $\overrightarrow{u_L} = (0, 1, w)$, which are by definition tangent to the function F_1, are included in $\mathscr{H}$. In intensive form, $\overrightarrow{u_k}$ is the resultant of $\overrightarrow{u_L}$ and $\overrightarrow{u_K}$ in the coordinate system (k, y) and is aligned with the line $(M_{\lambda_K} M_{\lambda_L})$ ((Figure 3.4).

The two conditions boil down to one condition for λ_K: the vectors $\left(\overrightarrow{u_L}, \overrightarrow{u_K}, \overrightarrow{OM_{\lambda_K}}\right)$ are coplanar. It means that their determinant is null,

$$\begin{vmatrix} 1 & 0 & \dfrac{K_0}{1+\lambda_K} \\ 0 & 1 & L_0 \\ r_1 & w_1 & Y_0 \end{vmatrix} = 0. \tag{3.9}$$

Lambdas expressions Hence,

$$\lambda_K = \frac{-Y_0 + r_1 K_0 + w_1 L_0}{Y_0 - w_1 L_0}. \tag{3.10}$$

Likewise,

$$\lambda_L = \frac{-Y_0 + r_1 K_0 + w_1 L_0}{Y_0 - r_1 K_0}. \tag{3.11}$$

Definition 4 (Bias)**.** Technical change is called *capital-biased* if the labour-saving component is larger than the capital-saving component: $\lambda_L > \lambda_K$, or *net labour-saving.*[9]

Step 3: Inputs allocation

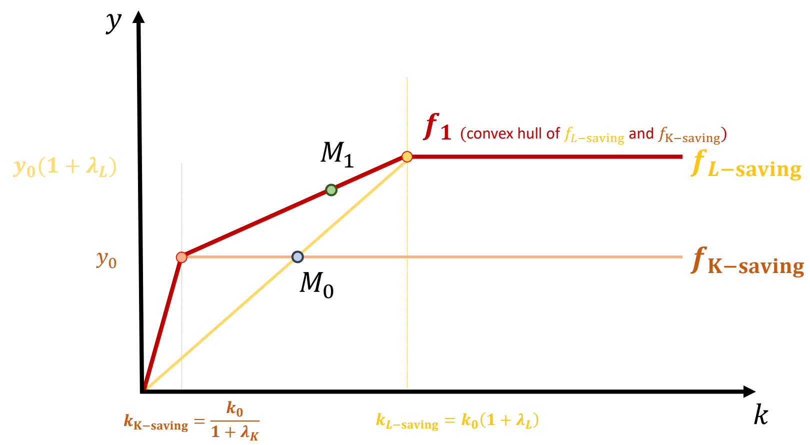
We apply the Proposition 1 to this situation: we can build a global production function F_1 by allocating inputs to one or to both of the local production functions $F_{\lambda_K}(K, L)$ and $F_{\lambda_L}(K, L)$ (these functions intersect in M_0).

[7] Without loss of generality. The demonstration is easily adaptable if F_1 is equal $F_{\lambda_K}(K, L)$ or $F_{\lambda_L}(K, L)$.

[8] In the extensive framework (Y, K, L), since all the (K, L) such as $K/L = k_0$ or $K/L = k_0'$ define the intersection between the functions F_0 and F_0' and the plan $\mathscr{H}$, it means that the origin belongs to $\mathscr{H}$. In 2D, we work in a plane obviously containing all the aforementioned points.

[9] Note that the meaning of the bias refers to Hicks (1932). It is equivalent to Acemoglu (2002) but we do not define factor-augmenting technical change.

Figure 3.5 – Step 3 — Inputs allocation



To reach Y_1 the inputs K_1 and L_1 are allocated to the two functions $F_{\lambda_K}(K, L)$ and $F_{\lambda_L}(K, L)$. The allocation is defined by (β_K, β_L) as follows:

$$\begin{cases} \beta_K \cdot \dfrac{K_0}{1+\lambda_K} + \beta_L K_0 = K_1 \\ \beta_K L_0 + \beta_L \cdot \dfrac{L_0}{1+\lambda_L} = L_1 \\ F_{\lambda_K}\left(\beta_K \cdot \dfrac{K_0}{1+\lambda_K}, \beta_K L_0\right) + F_{\lambda_L}\left(\beta_L K_0, \beta_L \cdot \dfrac{L_0}{1+\lambda_L}\right) = Y_1. \end{cases} \tag{3.12}$$

To ensure that the production function contains the point M_1 (point 1), we define the input allocation between the two factor-saving production functions as the solution of equation (3.12). It emerges that the allocation of resources (β_K, β_L) between the two production functions is given by:

$$\begin{pmatrix} \beta_K \\ \beta_L \end{pmatrix} = \begin{pmatrix} \dfrac{(1+\lambda_K)(-K_1 L_0 + K_0 L_1 (1+\lambda_L))}{K_0 L_0 (\lambda_L + \lambda_K + \lambda_L \lambda_K)} \\ \dfrac{(1+\lambda_L)(-K_0 L_1 + K_1 L_0 (1+\lambda_K))}{K_0 L_0 (\lambda_L + \lambda_K + \lambda_L \lambda_K)} \end{pmatrix}. \tag{3.13}$$

Summary

We need four parameters to describe how the production function F_0 in $M_0(Y_0, L_0, K_0)$ has shifted into F_1 due to technical change to now produce Y_1 using (K_1, L_1):

- λ_K and λ_L the intensity of the labour-saving and capital-saving technical change of the respective local functions (intensity of the deformation in the factor-saving direction),[10]
- and, β_K and β_L, the allocation of resources to each of the local functions to maximise production: β_K to the capital-saving function and β_L to the labour-saving function (3.12).

Note that if λ_L is negative, it means that the production function is now labour-using. That is, relatively capital-saving, and vice-versa.

Successive iterations

We assume that in each period we define the technical change as the transformation of a Leontief production function into a piecewise linear production function – which is a Leontief function only in the case of a change focusing on a single input (i.e, if $\lambda_K = 0$ or $\lambda_L = 0$).

After each period, we "forget" about the two factor-saving Leontief and we use the point M_1 as the characteristic point of a new Leontief function. We can successively describe the transition from one production (Y, K, L) to another as a break-down into two components labour and capital-saving by starting at each period from a new function Leontief.

We can interpret the specification of technical change as the combination of two factor-saving shifts as the innovation of multiple firms in a single direction, either labour or capital-saving: the new global production function reflects the new technology menu. As we start from a new Leontief function at each period, there is no path dependence in this framework.[11]

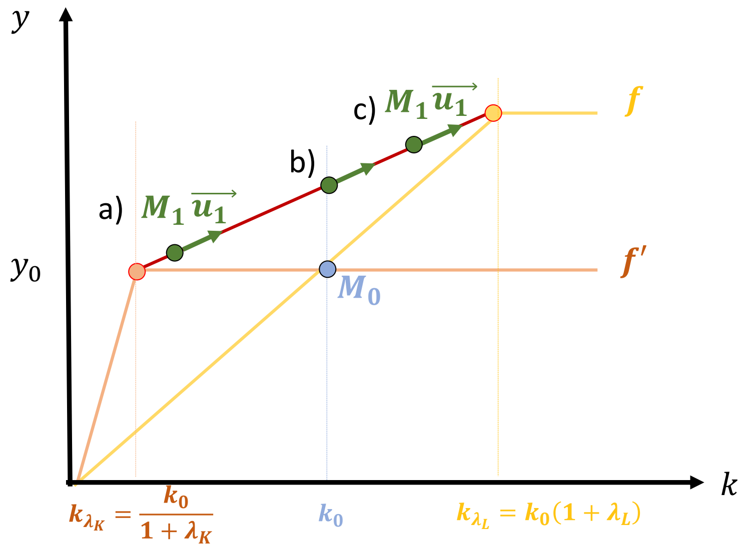
2.5 Growth and technical change accounting

We can easily see in equations (3.10) and (3.11) that k_1, the capital per worker at time $t = 1$, does not influence the intensity nor the direction of technical change (λ_L, λ_K). This is illustrated by the Figure 3.6 where the transitions from M_0 to different points M_1 have the same λ_L and λ_K. k_1 comes into play in the use of the factor-saving functions

[10] The choice of λ to represent the intensity of technical change in a certain direction is consistent with the nomenclature of Klump et al. (2007) where the λ represent the curvature of the Box-Cox transformation and the speed of a labour- and capital-augmenting technical change.

[11] We can interpret in several ways the absence of path dependence. We may assume that the firms aggregated in the Leontief production function at $t = 0$ are the ones innovating. New firms entering the market at $t = 1$ have no reason to define themselves with respect to the previous production function: they adopt the technology mix of $t = 1$, participate in Y_1, K_1 and L_1 as the previous firms at $t = 0$. Conversely, we may consider that new firms entering the market bring new technologies either labour or capital-saving while the incumbent firms have fixed technologies. At the end of the period, the technology mix has evolved: some incumbents have left the market and the remaining have adopted the new technologies. F_0 is no longer used by any firm. As previously, it makes sense to start again from a Leontief production function at the next period to get rid of any reference to F_0.

Figure 3.6 – Substitution versus Technical change



Note: Three situations a, b and c where M_1 is more or less capital-intensive give the same λ_L and λ_K, that is the same technical change bias. The phenomenon leading from situation *a* to *b*, *a* to *c*, or *b* to *c* is not technical change but pure capital deepening.

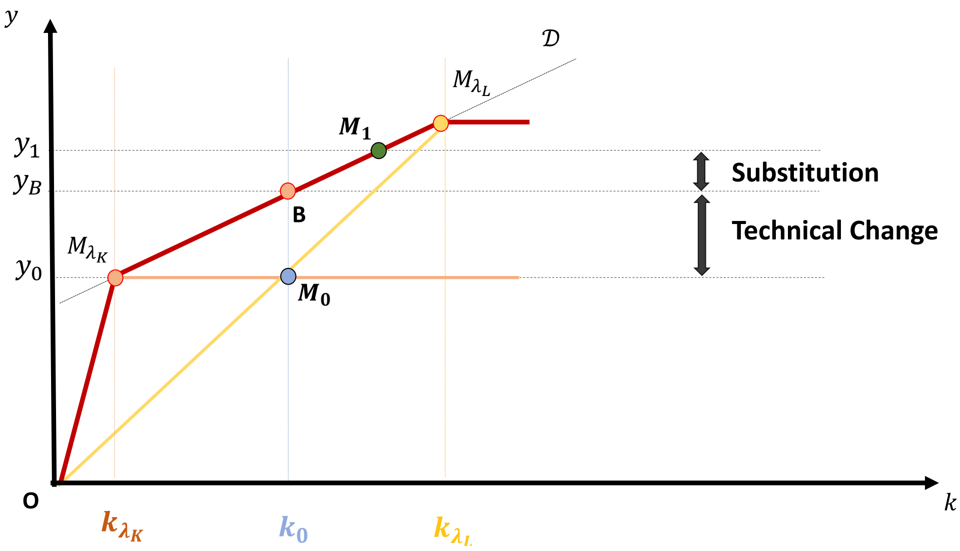
via the βs (eq. (3.13)). It is then easy to distinguish capital deepening from technical change. Technical change is any shift of the production function while capital deepening is the movement along the production function. The very fact that F_1 is not a Leontief production function ensures that we can have some substitution between L and K in our model.

The function f_0 is used at the point M_0, and the technical change explains how the production shifts to M_1. We explain the growth of output per worker y_0 to y_1 due to technical change and substitution between factors. We call B the intersection point between the vertical line in $k = k_0$ and the line $\mathscr{D}$. (Figure 3.7). The quantity $(y_B - y_1)$ does not depend on k_1, it is pure technical change as it depends only on λ_K and λ_L: it is technical change. The quantity $y_1 - y_B$ is a movement the function F_1 that depends solely on k_1: it is substitution. We call *capital-deepening* an increase in the ratio capital to labour and *capital-widening* a decrease of the ratio capital to labour.

Note that this quantity is based on the slope of the production function in this point (since the global production function is piecewise linear, the slope between the two characteristics ratio k_{λ_K} and k_{λ_L}. This slope is determined using the factor share to calibrate the model in equation (3.8). It plays the role of the elasticity of substitution in CES production functions. We are able to disentangle technical change and substitution because we take this parameter into account to build the framework.
We can express the two conditions using the equation of $\mathscr{D}$:

$$\mathscr{D} : y \mapsto \frac{y_0}{k_0} \frac{\lambda_L(1+\lambda_K)}{\lambda_L + \lambda_K\lambda_L\lambda_K} \cdot k + y_0 \frac{\lambda_K(1+\lambda_L)}{\lambda_L + \lambda_K\lambda_L\lambda_K}. \tag{3.14}$$

Figure 3.7 – Growth accounting decomposition for output growth in an intensive framework



The technical change contribution is:

$$\frac{y_B - y_0}{y_0} = \frac{(\lambda_K + \lambda_L + 2\lambda_K\lambda_L)}{(\lambda_K + \lambda_L + \lambda_K\lambda_L)} - 1. \tag{3.15}$$

The capital deepening contribution is:

$$\frac{y_1 - y_0}{y_0} = \frac{y_1}{y_0} - \frac{(\lambda_K + \lambda_L + 2\lambda_K\lambda_L)}{(\lambda_K + \lambda_L + \lambda_K\lambda_L)}. \tag{3.16}$$

Note that this framework can accommodate a variety of situations, including pure substitution. If any of the λ is nil, then the contribution of technical change to output per worker growth is zero, and the substitution contribution is 100%. It also means that a hugely biased technical change is likely to be more substitution than actual technical change.

3 Data

To put our framework to the test of observations, we use sectoral data from the U.S. KLEMS database built by the BEA (version 2020) and the EU+ KLEMS database (versions 2008, 2017 and 2021). Table 3.1 describes the four databases in terms of observations, sectors and countries.

The U.S. KLEMS provides price and quantity measures for output and inputs in 61 NAICS industries and 20 aggregate sectors from 1986 to 2019. From now on, we will refer to these 81 sectors as industries or sectors indifferently. Capital cost is a flow of capital services taken as an exogenous share of the Fixed Capital asset quantity. We derive input share as the share of the cost of one factor. Prices for each factor are included in the table for each industry. We use current values as it allows us to express input share easily without the usual bias from economic deflators such as Laspeyres, Paasche or Fisher. Since we use only two inputs — capital K and labour L —- we consider the value-added of each sector, which is the sectoral output minus the cost of Intermediate Inputs. In pure and perfect competition, pure profits amount to zero which ensures that α_L the labour share and α_K the capital share sum to one. Quantity indexes are computed for inputs and output as the ratio of expenses in current dollars and price indexes.

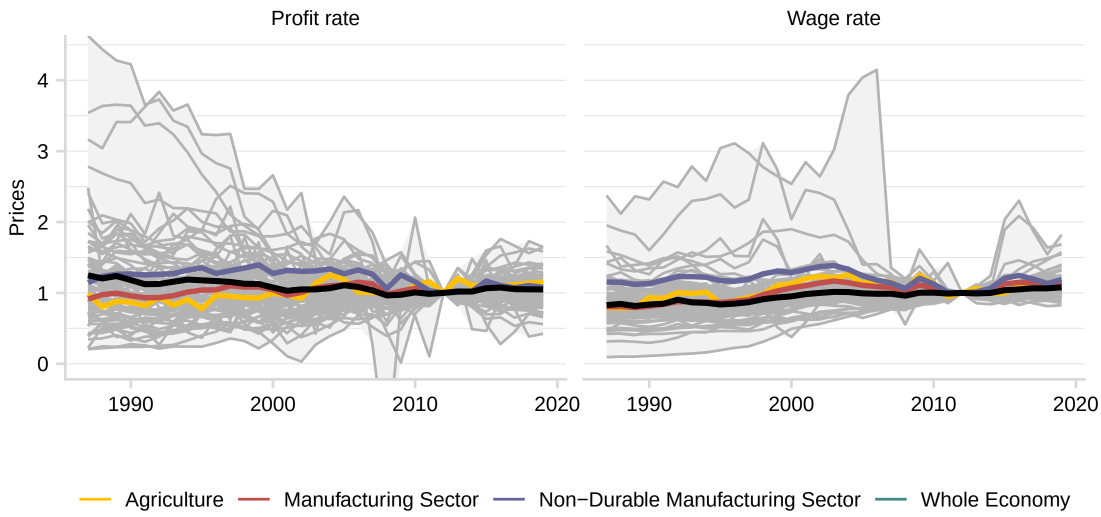
As a consequence of the previous computation, we ensure that the shares of inputs sum to one, $\alpha_L + \alpha_K = 1$, and that each sector input-output sheet is balanced, $Y = wL + rK$ with w and r, respectively the wage — the unit cost of labour — and the profit rate — the unit cost of capital. We also compute $r = \alpha_K Y/K$ and $w = \alpha_L Y/L$, which translate into factors being paid at their marginal productivities.

The EU+ KLEMS database version 2021 (Stehrer, 2021), version 2017 (Van Ark and Jäger, 2017), and version 2008 (Timmer et al., 2007) provide capital and labour compensations in millions of national currency (CAP, LAB); capital services and labour services in volume indexes (CAP_QI, LAB_QI, index 100 in 2010); output and intermediate inputs in current national currency (GO, II) and volumes (GO_QI, II_QI); and their prices indexes (GO_P, II_P). For labour and capital, we compute prices as the ratio of compensation and quantities. We check that this method provides the right price as indicated for output and intermediate output in the database. We compute value-added for each industry. We only keep series for which the listed variables are present for at least 4 consecutive years.

EU+ KLEMS v2008 span over 1970-2005 for a number of countries and industries, using SIC nomenclature. The time series are of variable size. EU+ KLEMS v2017 and v2021 classify industries according to the NACE classification, respectively for 1997-2015 and 1997-2019. We only keep series from the v2017 when the industry for a country is not available in the 2021 database (see Table 3.1, 28 countries in v2017 versus 21 in v2021). The U.S. data are present in the EU+ KLEMS database for a SIC and a NAICS aggregation. We check along the process that we get similar trends in prices, quantities and technical change indexes for the comparable industries within EU+ KLEMS and U.S. KLEMS database.

In section 4.2, we try and gather the time series of a same industry in a same country on a same graph. The perimeters and the methods used are only partly compatible. We present trends in technical change across the 3 databases for European countries for two sectors in the appendix 3.D, figure 3.D.9 and figure 3.D.11.

Figure 3.8 – Prices for all 81 U.S. industries



Note: Prices normalised to 1 in 2015. Macro prices are aggregated using gross output data.

Table 3.1 – Description of the databases

	KLEMS EU+ v2008	KLEMS EU+ v2017	KLEMS EU+ v2021	KLEMS U.S. v2021
Number of observations	17,844	7,934	12,841	5,184
Number of time series	781	482	733	81
Number of industries	107	41	57	81
Number of countries	31	28	21	1
Average length of time series	22.8	16.4	17.5	32
Max length of time series	35	33	24	32
Min length of time series	35	33	24	32
Average industries per country	37.2	32.1	38.6	81
Max industries per country	38	40	55	81
Min industries per country	30	9	1	81
Average countries per industry	20.6	12.05	13.3	1
Max countries per industry	21	15	19	1
Min countries per industry	19	5	6	1

Note: The 2008 version of KLEMS EU+ covers a number of European and non-European countries (Australia, Japan, USA). The 2017 and 2021 versions cover the period 1997-2015 and 1997-2019 respectively. These two databases include European countries and the United States. For the 2017 version, only the industry and country pairs not present in the 2021 database with longer series are retained.

4 Technical change overview: a U.S. and European perspective per industry

We apply the framework detailed in section 2.4 to the KLEMS databases. We compute λ_L, λ_K, β_L and β_K per industry with equations (3.10, 3.11, 3.13).

4.1 United-States Technical Change

Figure 3.9 plots the relative direction of technical change for 20 U.S. industries between 1986 and 2019. The relative direction of technical change is the ratio between the intensity of net labour-saving and capital-saving technical change, λ_L/λ_K. When this indicator is larger than unity, it indicates labour-saving technical change (capital bias), when it is lower than unity it indicates net capital-saving technical change (labour bias).[12]

The first result is that all industries have non-zero labour-saving and capital-saving technical change. Both directions of technical change are experienced throughout the period. Second, there are large differences among industries. Of the 20 industries represented, 6 are net labour-saving for at least a year, meaning that the others may save on labour but less than on capital.

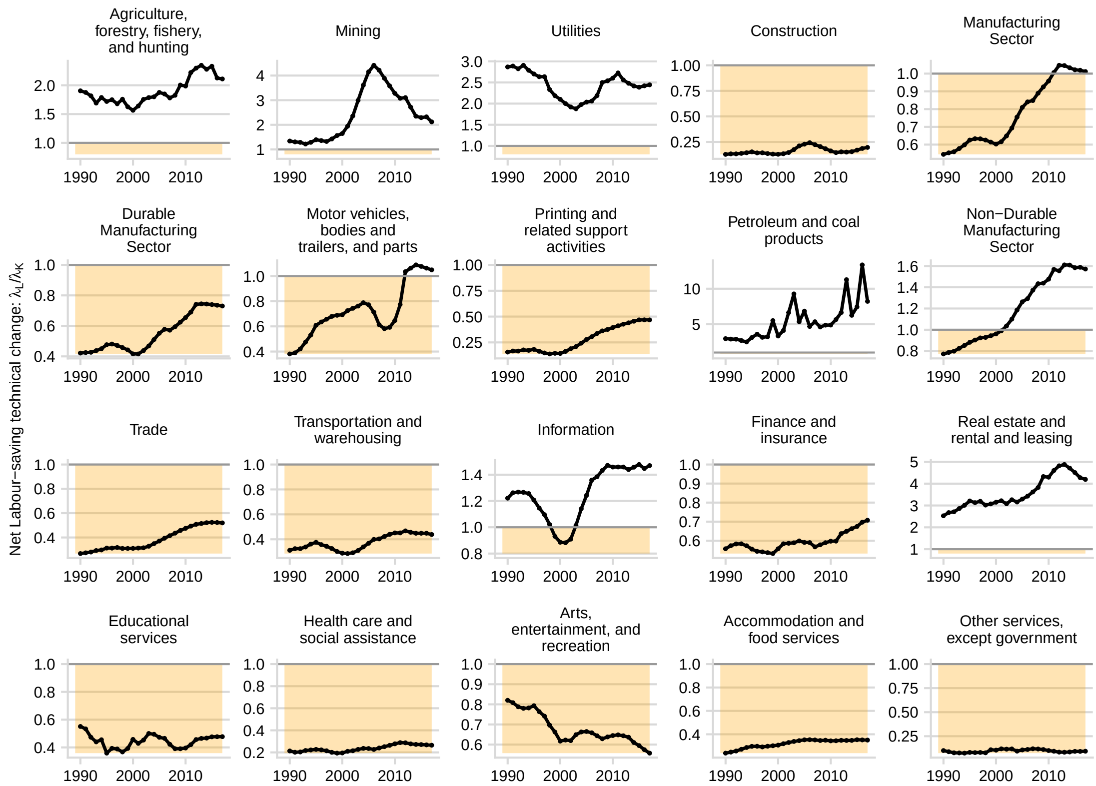
We will focus on some industries to link the dynamics of the relative direction of technical change to specific technologies and innovations. We will use the growth accounting framework to distinguish technical change from substitution of capital for labour.

Manufacturing sector Technical change in manufacturing is net capital-saving in the first part of the period (90s and 00s). It shows an increasing trend towards net labour-saving technical change, which was reached in the 2010s (Figure 3.9). After the economic crisis in 2008, technical change has been factor-using, showing negative λs: the industry under-utilised its capital and labour inputs due to the demand shortfall, which shows up in our technical change statistics as technical regress.

Thus, the main reason for the decline in U.S. manufacturing jobs since 2001 is not massive labour-saving technical change. Pierce and Schott (2016) provides evidence for 2 main mechanisms explaining job losses: supply-chain disruption and technical change. Supply-chain disruption can be caused either by more Chinese imports in the U.S. for inputs or final products, by the off-shoring of U.S. production or by the relocation of other non-U.S. manufacturing (e.g. European manufacturing partners off-shoring their production in China). The induced technical change identified by Pierce and Schott (2016) is actually a movement of relative capital deepening. Fort et al. (2018) shows within-firm employment declines due to plant closures and technology adoptions.

[12] We remind the reader that the net direction of technical change is merely the ratio of the intensities of the two input-saving production functions. It would be presumptuous to conclude about the evolution of factor shares, since two other parameters come into play: the use β_L and β_K of the two input-saving production functions.

Figure 3.9 – Net Labour-saving technical change λ_L/λ_K on 20 aggregate U.S. industries



Note: The intensities of technical change are computed on price and quantities of inputs averaged over a rolling 5-year period. In the appendix, Figure 3.C.7 shows that the trends of this indicator are identical on annual data or with a rolling average period of 3 or 5 years.

Indeed, manufacturing output per worker increased rapidly between 1995 and 2005, then slowly up to 2019 (Table 3.2). The decomposition of this growth shows a larger contribution from capital deepening, i.e. pure substitution, than from technical change, except in the 1995-2005 decade, when automation develops strongly due to the massive introduction of robots (Acemoglu and Restrepo, 2020).

Automotive industry By the end of the 90s, U.S. plants had already almost 100% automated bodywork[13] manufacturing plants (as well as Japanese and European automakers), whereas assembly lines had remained little automated. Firms were relying on lean management (both capital and labour-saving) to increase productivity. Indeed,

[13] Definition: the bodywork is "the main outside structure of a vehicle, usually made of painted metal", Oxford Dictionary.

Table 3.2 – Growth, substitution, capital and labour-saving technical change accounting. U.S. Manufacturing sector

Year	Growth of output per worker	Technical change component	Substitution (capital deepening)
1990-1994	0.09	0.04	0.05
1995-1999	0.15	0.10	0.05
2000-2004	0.22	0.11	0.11
2005-2009	0.07	-0.01	0.08
2010-2014	0.03	-0.05	0.08
2015-2019	0.10	0.08	0.02

Note: The data is aggregated over a 5-year period to clarify results and trends.

in a context of economic slowdown, over-automation and over-investment made it difficult for factories to be profitable (Krzywdzinski, 2021). Therefore, contrary to popular belief, the automotive sector is clearly saving capital to increase its resilience and profitability. Between the late 1990s and the mid-2010s, there has been little automation in the sector. Since the mid-2010s, assembly line automation has increased, largely due to the rise of the electric car, which is easier to assemble. We can pinpoint both the net-labour saving surge of technical change in the automotive industry and the strong component of technical change in the growth of output per capita over the 2015-2019 period (Table 3.C.5).

Non-Durable manufacturing Overall, non-durable manufacturing shows a strong progression from net-capital saving to labour-saving technical change. This trend is largely driven by a few sectors: food and beverage and tobacco products, chemicals, and especially petroleum and coal products.

Oil and gas sector The technological evolution of the fossil fuel sector in the U.S. has been disrupted by the exploitation of shale gas in the U.S. from 2007-2009.[14] The exploitation of shale gas and oil is much more labour-intensive than the exploitation of conventional wells. Indeed, it requires a vertical well — to reach the deposit — and then a horizontal drill — through the entire deposit. It requires labour to drill and evacuate the waste (truck drivers). The new shale gas drilling and extraction techniques are more labour-using and capital-using than conventional industries. The λs are both negative over the period — indicating input-using technical change. Furthermore, the decomposition (Table 3.C.6) does indicate a negative component of technical change in output per worker between 2005 and 2014, offset by an increase in capital per worker. The end of the period (2015-2019) shows the setback suffered by the U.S. oil industry

[14]Production increased by +54% between 2007 and 2008, +74% between 2008 and 2009 (EIA Data).

when the price of the barrel fell. The industry laid off massive numbers of workers (200,000 in 2014-2016 (Insights, 2020)), resulting in an artificial increase in production per worker and a "labour-saving technical change", that in reality corresponds to a period of exploitation and no longer a period of new drilling.

Clerical & Administrative sectors The clerical and administrative sectors[15] are largely net capital-saving, against all expectations. The level of λ_K is somewhat high, probably reflecting the declining cost of computers and software. It might also capture some economic rent — due to the monopole of clerks on some legal actions, e.g. French notaries for inheritance and sales of real estate — as our framework makes the hypothesis of pure and perfect competition and turns a blind eye on positive profits.

Agricultural sector The agricultural sector is largely net-labour saving over the entire period (Figure 3.9). The labour-saving trend is greater than in almost all other sectors. Along with Herrendorf et al. (2015) we find significant intensities of technical change towards both capital- and labour-saving directions. Between 2000 and 2005, agricultural output per worker boomed (+27%) and technical change accounted for the largest share of this growth (+21%) compared to capital deepening (+5%). However, apart from this period, there has been little growth in output per worker, low technical change — even though it remains net labour-saving — and a low positive capital deepening (See appendix 3.C, Table 3.C.3).

Gallardo and Sauer (2018) provides an overview of labour-saving innovations in the agricultural sector. We mention some of them: of course, the mechanisation of harvesting, sowing or ploughing. A fully automated system for fruit harvesting does not yet exist and would allow significant labour savings. Let us also mention irrigation systems (which, for example, played an important role in improving agricultural productivity in Japan long before mechanisation), guidance systems, and even autonomous vehicles. In livestock farming- where the tendency to save labour is even more pronounced than in agriculture in general — we are talking about improving milking and milk storage techniques, increasing animal density on farms, automated slaughterhouses, and automated health monitoring.

Other innovations are more directly capital-saving, such as the pooling of machinery made possible by the restructuring of farmland and the increase in the average size of farms, the extension in the lifespan of machinery and its ability to be repaired, and the decrease in the price of certain technological innovations (computers, GPS, etc.). Another trend is the reduction in the risk taken by farmers: the use of crop protection through phytosanitary products makes it possible to limit the frequency and extent of crop failures. With a more steady income, the cost of bank loans and investments decreases.

[15]They are not shown in figure 3.9. They include: Management of companies and enterprises (55); Administrative and waste management services (56); Professional, scientific, and technical services (54).

A range of technologies, species selection, genetic modification, pest and disease control do not imply more labour-saving than capital-saving technical change (apart from the reduction in risk), but overall improve the productivity of both inputs.

The historical automation of the agricultural sector is not clearly explained in the literature: mechanisation implies adapting to a changing environment, performing a wide variety of tasks to be profitable and combining approaches from multiple disciplines. However, one of the reasons often cited is the historical dependence on imported labour — currently from Mexico — which is greater than in other sectors. Waves of immigration-restrictive policies have then driven technological progress. For instance, since 2008, labour supply in U.S. farms has been declining because i) immigration, especially illegal immigration, has been limited, ii) the U.S. farm sector is competing with the Mexican farm sector and the growth of Latin-American economies, and iii) the American farming workforce is ageing. The combination of these reasons leads to the adoption of less labour-intensive technologies and management practices (Taylor et al., 2012; Zahniser et al., 2012; Gallardo and Sauer, 2018).

Printing industry The publishing industry requires heavy investment, especially in printing presses. With the printing industry, we can pinpoint the specific technologies that are reflected in the outlined directions of technological change. In the early 1990s, the first digital photocopiers appeared on the market. In 1996, the first digital press to be used in a professional printshop was released[16] to replace older technologies such as lithography and gravure (Dunn et al., 2001). The trend towards net capital-saving of the industry intensifies in the second half of the 1990s. The trend continues today, albeit with less and less net capital saving. This is due to a decrease in the capital-saving intensity of technical change more than to a rise in labour-saving technical change. The contribution of technical change to growth in value-added per worker has also been declining since the 2010s (See appendix 3.C, Table 3.C.2).

Health sector The health sector can hardly do without staff, hence it is mainly capital-saving (optimisation of beds and machines, centralisation in large hospitals and economies of scale, etc.). The growth of production per worker is naturally low but is supported by a regular substitution of capital for labour. The contribution of technical change to this growth is small and erratic (See appendix 3.C, Table 3.C.7).

Information industry The information industry includes broadcasting and telecommunications, Internet publishing, and software. The rise of the Internet in the early 2000s was due to strong capital investment rather than technological advances. Since 2010, the sector's growth has been largely supported by capital deepening (See appendix 3.C, Table 3.C.4). The second half of the 2000s saw a strong net capital-saving technical shift (Figure 3.9) that can be linked to the rise of search engines (Google was founded in 1998) and the launch of Web 2.0 in 2004.

[16]The Four-Colour Indigo Press, followed in 2001 by the Colour Docutech 2060 has doubled the production per minute (Dunn et al., 2001).

The U.S. industries with the highest λ_L/λ_K ratios are also the sectors where the labour share is the lowest, and thus the most capital-intensive (see Appendix, Figure 3.C.8).

For each pair $\lambda_{K,L}$ — the intensities of technical change — we compute the allocation of inputs to the factor-saving functions: $\beta_{K,L}$. For 69% of the observations, we obtain a pair of positive β. This means that our model does not provide a satisfactory representation of technical change for 30% of the observations. Indeed, a negative β means that we use a production function with negative inputs — which is, of course, physical nonsense. We can put forward two hypotheses. The first is that we are capturing a phenomenon beyond technical change: a disruption of some kind, such as a strike, or geopolitical developments in the sector, or a measurement error (or a change in scope, etc.). The second hypothesis is that the technical change is too large and beyond our methodology.

The concentration of negative beta in a few years (50% of unexplained observations are concentrated in 10 years out of a sample of 32) suggests a common (macroeconomic) cause. The years in which these observations are concentrated follow exactly the major economic crises since 1987. The top 6 in terms of unexplained observations — between 39.5 and 45% of industries are poorly captured — are: 2019 (2018 was the worst year for stocks since the 2008 financial crisis); 2002 (following 9/11, major economic disruption); 2009 (following the subprimes crisis); 1990 (following the 1989 Savings and Loan crisis); 1999 (following the Asian crisis); 2001 (following the dot-com bubble burst). During a crisis, demand falls sharply, firms under-use their factors of production temporarily worsening productivity and causing a factor-using technical change. Therefore, in the following year, there is a double rebound summing the return to normal trajectory and regular technical change: one of the β skyrockets, condemning the other to be negative to balance it out. The fact that the λs do not deviate from the trends of these sectors[17] suggests that the problem is not the intensity of technical change, but that we are capturing a broad effect of "technical change" on fuzzy data in a world where the *ceteris paribus* is just an illusion.[18]

4.2 European Technical change

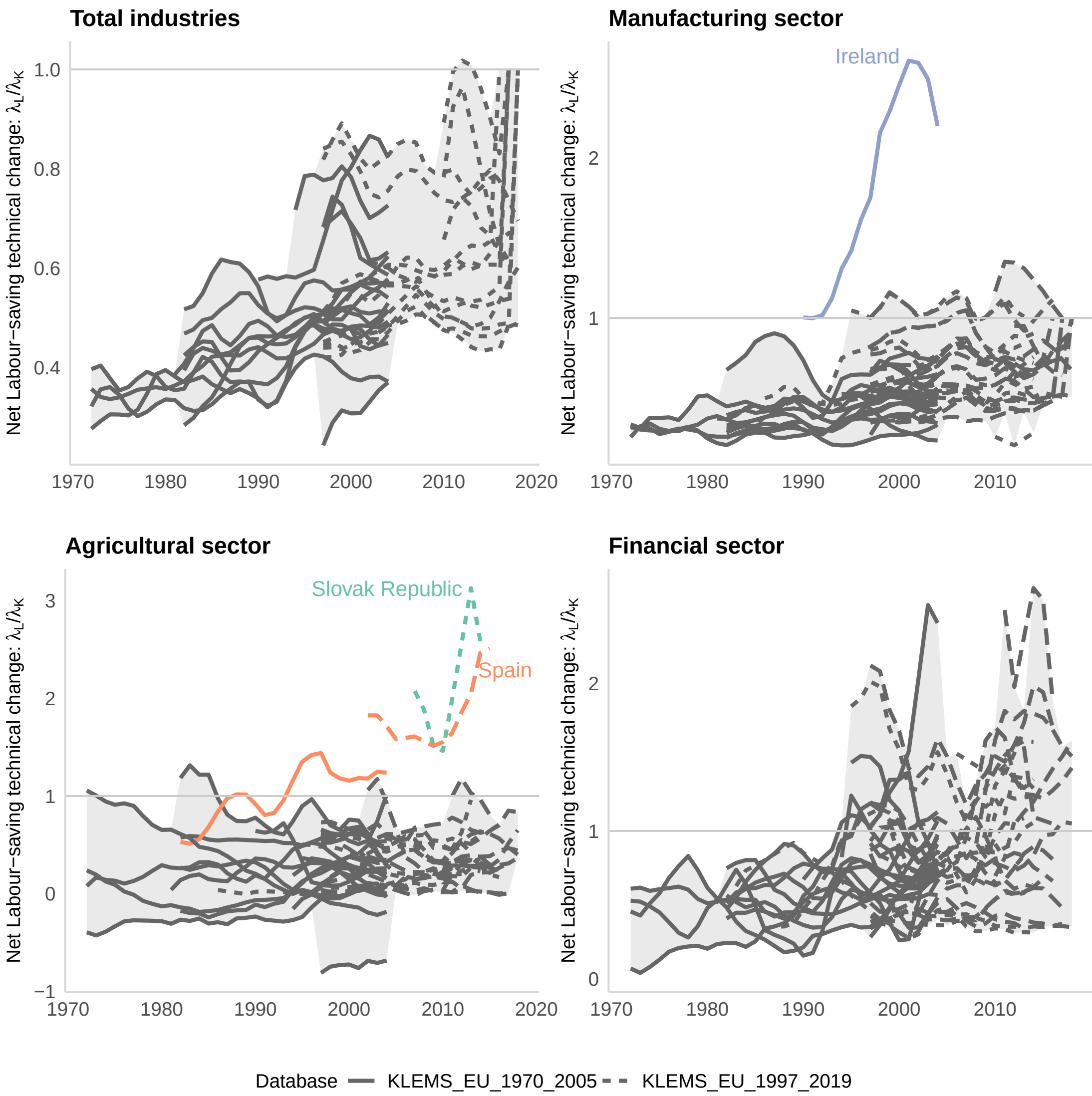
At the national level, European economies are still predominantly capital-saving,[19] but the figure shows a clear trend towards increasingly labour-saving technical change from 1970 to 2019 (Figure 3.10). Utilities and the real estate sectors are clearly labour-saving in all countries. Other sectors, including construction, trade, public administration, education and health care are net capital-saving. The financial and manufacturing

[17] Note that the trend of the λ_L/λ_K ratio are unchanged if we exclude these points. Similarly, the analyses in the following sections are unchanged if we exclude negative βs.

[18] Interpolating the data to reduce the time step does not give better results, there are still jumps too large to be captured. The solution would be to improve the temporal or sectoral granularity.

[19] In contrast to the U.S. KLEMS database, KLEMS EU+ already provides aggregate data for total industries for each country. Hence there is no need to test for several aggregation rules.

Figure 3.10 – Net Labour-saving technical change (λ_L/λ_K on 4 industries for KLEMS EU+ (two databases))



sectors follow the same trend as the overall production: net capital-saving with a growing labour-saving trend. The financial sector has even been net labour-saving in a number of countries since the mid-1990s. A notable exception to the manufacturing sector being capital-saving is the case of Ireland, which shows a very high degree of labour-saving technical change from the early 1990s.

Labour-saving technical change in Ireland is the result of imported innovation – technology transfer – particularly from the United States, which has been the country's largest foreign direct investor. These innovations have been located in certain high-technology sectors – such as chemicals, publishing, and software, as well as electrical and optical equipment – whose productivity per worker exploded during this period (Cassidy, 2004). The Irish economy has specialised in these industries. Manufacturing employment did not increase during this period but was concentrated in these specific manufacturing industries. Another factor in explaining the increase in labour-saving technical change net of capital-saving technical change is that the Irish economy is not at all in a capital-saving trend at this time (very low λ_K). Apart from technology transfers, U.S. investment led to the accumulation of physical capital, while the government made up for the deficit in infrastructure.

In contrast, the agricultural sectors of European countries are predominantly capital-saving, with no discernible trend towards net labour-saving since the 1970s. Labour-saving innovations in the agricultural sector are mainly mechanisation, which peaked in the U.S. and Europe before the 1970s, and thus before the beginning of the series studied in this chapter. Europe, unlike the U.S., still has access to cheap immigrant labour for its agricultural sector, which might explain the lower labour-saving technical change.

There are two exceptions to the capital-saving trend in agricultural sectors. Spain and the Slovak Republic exhibit a highly net-labour saving agricultural sector.

Slovakia significantly increased the productivity of its agricultural sector between 1995 and 2012 — despite a decline in the share of agriculture in GDP (Kotulič et al., 2014). The determinants of productivity growth are both structural and financial. After 1989, Czechoslovakia implemented a number of reforms, including the liberalisation of trade and the adoption of a market economy, as well as reorienting the economy away from Soviet Union priorities through the development of the private sector (Maris, 2019). These reforms were pursued by the Slovak Republic in view of its accession to the European Union. After joining the European Union in 2004, the subsidies of the Common Agricultural Policy enabled the modernisation of the Slovak agricultural sector from labour-intensive to relatively more capital-intensive (Némethová and Civáň, 2017).

The case of Spain is more delicate. The case studies on the Spanish agricultural sector do not give a clear picture of how this sector is developing. Low-skilled migrants account for an increasingly large share of workers in Spanish agriculture. This participation tends to lower average hourly productivity (Kangasniemi et al., 2012). Similarly, the use of temporary employment contracts dampens productivity (Ortega and Marchante, 2010). González and Ortega (2011) shows that immigration increases the use of low-skilled labour and hypothesises that firms adapt by adopting less advanced technologies (Lewis, 2005). Spain experienced a period of great technical change in agriculture between the 1960s and the 1980s, thanks in particular to the use of chemical inputs but above all to a high level of mechanisation (the number of harvesters, tractors and cultivators increased by a factor of 9, 18 and 123 respectively between 1960 and 1985) (Molina et al., 2016). However, this growth in mechanisation has been lower since the beginning of the 21th century, and clearly lower than in France for example.[20] Compared to other European countries, Spain and Austria even experienced a technological regression in the agricultural sector between 2006 and 2017 (Smędzik-Ambroży and Sapa, 2019). All these reasons should lead to labour-using technical change in Spain while we witness a labour-saving in our indicators.

The ratio λ_L/λ_K captures only the technical change bias. In the case of the Spanish agricultural sector, both labour- and capital-saving technical change are small in absolute value (Appendix 3.D, Figure 3.D.10) – and sometimes both negative – the resulting technical change is small but net-labour saving.[21] In contrast, France, Germany and the UK are largely capital-saving and have a high degree of technical change.

Using the ratio λ_L/λ_K also fails to distinguish the case of Slovenia with labour-saving and capital-using technical change over almost a decade from 1992 to 2004.

4.3 Full Economy — U.S. & Europe

We focus on the direction of technical change across the economy rather than by sector. The U.S. KLEMS database does not provide data at the national level. Then, we aggregate the labour-saving or capital-saving character of all sectors to conclude the direction of the economy. We test several aggregation rules with various weights for each sector: share of annual GDP, share of 2019 GDP, share of total employment, and share of national income.

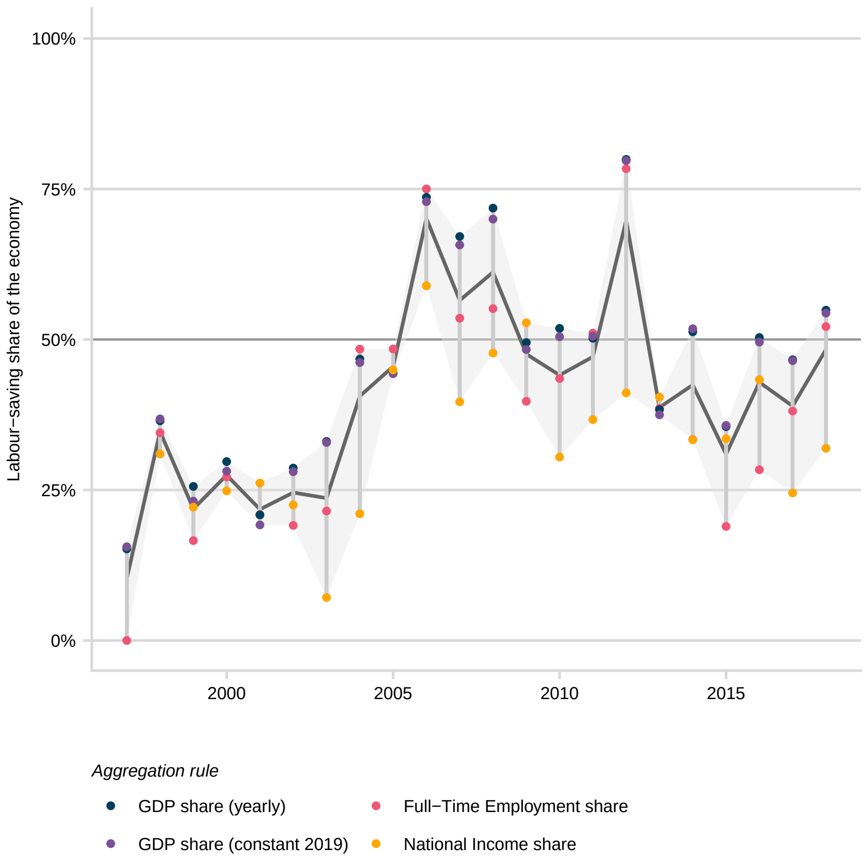
Whatever the aggregation rule, the U.S. economy is slightly more capital-saving than labour-saving (Figure 3.11): the American economy is labour-biased. Since the end of the 1990s, the economy has tended to move closer to, and sometimes has exceeded, the 50% threshold of the labour-saving economy, depending on certain indicators. The series from the BLS are discontinuous and cannot be traced back before 1997 using the NAICS nomenclature of the KLEMS database.

Figure 3.12 shows the decomposition of growth in national value-added per worker into technical change and substitution of capital for labour, over 1970-2005 for 20 economies. In the United States and the United Kingdom, the technical change and substitution components were very close to each other in the 1980s and 1990s. In

[20]Statistics from the French and Spanish Ministries of Agriculture, new tractors registered in France and Spain (respectively): 2001, 35461 and 18314, 2006, 35136 and 16605, 2011, 38192 and 10002, 2016, 11426 and 11428, 2019 54617 and 12156. Note that the French population is about 45% larger than the Spanish population.

[21]For some years when technical change is labour- and capital-using, the total result is labour-saving if the capital-using change is more intensive than the labour-using dimension.

Figure 3.11 – Aggregate direction of the technical change of the U.S. economy

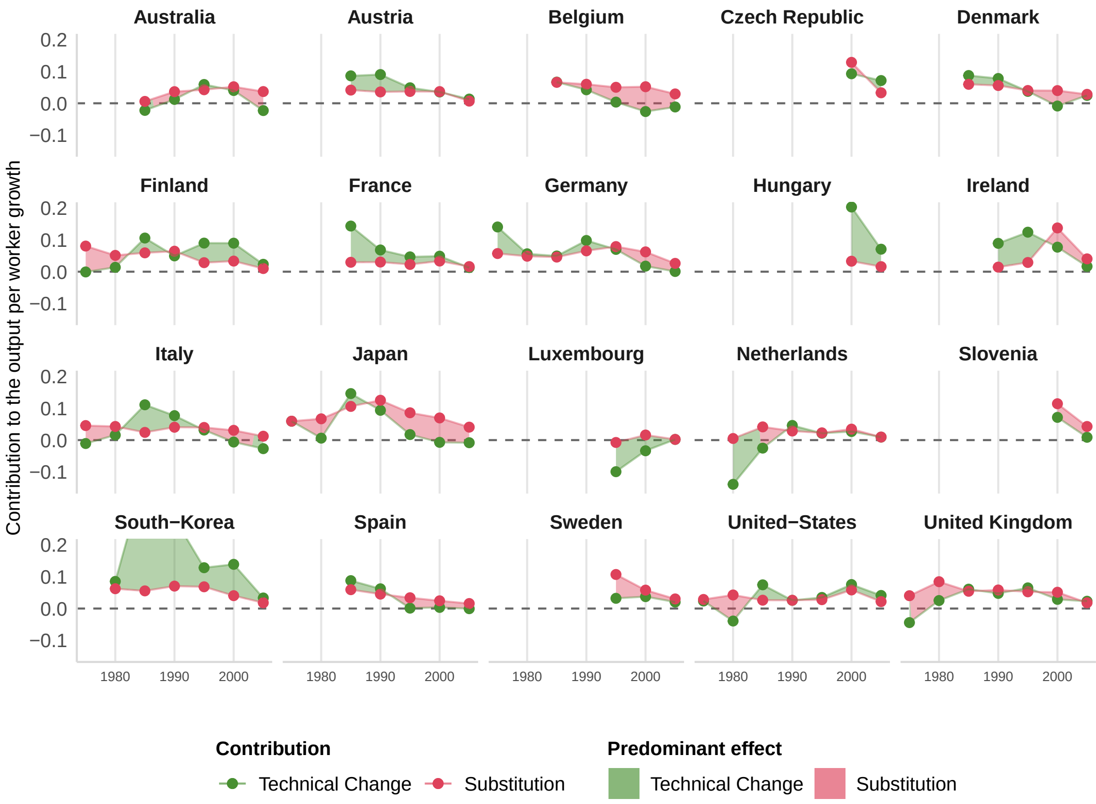


contrast, France experienced very low substitution but high technical change, as did Hungary and Ireland, Italy, Finland and Austria. South Korea also experienced striking growth in output per worker during this period, reflecting strong technical change.[22] Other countries such as Belgium and Sweden experienced a growth in output per worker supported by capital-labour substitution. Luxembourg and the Netherlands stand out with a negative contribution of technical change to growth (in this period, technical change is capital-using and even more labour-using).

Blanchard et al. (1997) cites 3 possible causes for the fall of wages during the 80s and 90s period: i) a shift in the distribution of profits between workers and capital holders, ii) labour-biased technical change and iii) substitution of capital for labour. We find that technical change has been net capital-saving in most European countries (Figure 3.10) and the U.S. since 1970, and there does not seem to be a major episode of substitution across the continent.

[22] This growth can undoubtedly be linked to the liberalisation of the economy and massive investment in industry in the 1980s, as well as the opening to foreign capital in the late 1990s.

Figure 3.12 – Substitution *vs* technical change component of output per worker growth at the national level 1970-2005



Note: The growth of output per worker is the sum of these two components. The predominant effect on the output per worker growth is considered to be the largest in absolute value. For clarity, data are aggregated at the 5Y timespan.

Our results seem to concord with Arpaia et al. (2009) which highlights both capital-deepening and capital-augmenting technical change in Europe. However, it appears to be in contradiction with the studies of Klump et al. (2007), which finds technical change to be labour-augmenting[23] in the U.S. between 1953 and 1998. We can put forward a few hypotheses on the source of these divergences. The first and simplest is that we are using different data sources over a more recent period. Secondly, Klump *et al.* estimate a long-term relationship, whereas we focus on the inter-annual short term, which may explain results consistent with theoretical predictions. In the long-run, technical change must be labour-augmenting, but in the short-run, both capital and labour-augmenting

[23] If capital and labour as supposed to be gross estimates, then labour-augmenting means capital biased and labour-saving.

technical change can coexist, so we are not in contradiction with the theoretical models since our λs represent annual directions of technical change.

5 New insights on Hicks's hypothesis

5.1 Definitions & Specifications

In this chapter we have computed the direction and intensity of technical change. It happens to be more or less labour or capital-saving across industries and countries. The question that naturally follows from this break-down is the following: why is there an asymmetry between the two directions of technical change? Can the difference in price increases explain it ? Here, we investigate the influence of price on technical change and the direction of technical change.

The most famous hypothesis, and also the most intuitive, is the Hicks's hypothesis of price determination of technical change. Hicks states that "*A change in the relative prices of the factors of production is itself a spur to invention, and to invention of a particular kind – directed to economising the use of a factor which has become relatively expensive.*" (Hicks, 1932). A silly example would be: if coffee was the new caviar we would be all drinking tea.[24]

Specifications

In this section, we test Hicks's hypothesis on the intensities of technical change derived in the previous sections, by inferring a relationship with the variations of the inputs prices. We produce four specifications for estimating the Hicks's hypothesis. ε represents the error of the estimation. We estimate either:

- the relationship between the relative direction of technical change on the evolution of relative prices:

$$\frac{\lambda_L}{\lambda_K} \sim \Delta \frac{w}{r} \Longleftrightarrow \frac{\lambda_L}{\lambda_K} = a_{w/r}^{L/K} \Delta \left(\frac{w}{r} \right) + \varepsilon, \tag{3.17}$$

  with $a_{w/r}^{L/K}$ the estimated coefficient;

- or the relationship between the relative direction of technical change and the evolution of prices

$$\frac{\lambda_L}{\lambda_K} \sim \Delta w + \Delta r \Longleftrightarrow \frac{\lambda_L}{\lambda_K} = a_w^{L/K} \Delta w + a_r^{L/K} \Delta r + \varepsilon, \tag{3.18}$$

  with $a_r^{L/K}$ and $a_w^{L/K}$ the estimated coefficients;

[24] Given that we might consider a researcher to be a machine that converts coffee into theorems, as Alfréd Rényi states, then coffee is an input in the production of knowledge. If it were to become too expensive, then it would be natural to substitute another exciting hot beverage: we would make do without an input that would have became too expensive or substitute another.

- or, the relationship between each direction of technical change and the evolution of relative prices

$$\begin{aligned} \lambda_L \sim \Delta\frac{w}{r} \Longleftrightarrow \quad \lambda_L = a^L_{w/r}\Delta\frac{w}{r} + \varepsilon \\ \lambda_K \sim \Delta\frac{w}{r} \Longleftrightarrow \quad \lambda_K = a^K_{w/r}\Delta\frac{w}{r} + \varepsilon, \end{aligned} \tag{3.19}$$

with $a^L_{w/r}$ and $a^K_{w/r}$ the estimated coefficients;

- or finally, the intensity of technical change separately:

$$\begin{aligned} \lambda_L \sim \Delta w + \Delta r \Longleftrightarrow \quad \lambda_L = a^L_w \Delta w + a^L_r \Delta r + \varepsilon \\ \lambda_K \sim \Delta w + \Delta r \Longleftrightarrow \quad \lambda_K = a^K_w \Delta w + a^K_r \Delta r + \varepsilon, \end{aligned} \tag{3.20}$$

with a^L_w, a^L_r, a^K_w and a^K_r the estimated coefficients.

Interpretations & Analysis strategy

To proceed with the test of Hicks's hypothesis, we present four interpretations of price-induced technical change (with the example of labour). We explain how they are reflected in the equations and announce the section in which we test this specific interpretation. Induced technical change can be understood as:

1. An increase in the cost of labour leads to relatively labour-saving technical change:
   Equation: $a^{L/K}_w > 0$ (eq. 3.18), **Results**: section 5.5
   Equation: $a^L_w > a^K_w$ (eq. 3.20), **Results**: section 5.8

2. A relative increase in the cost of labour leads to relatively labour-saving technical change:
   Equation: $a^{L/K}_{w/r} > 0$ (eq. 3.17), **Results**: section 5.6
   Equation: $(a^L_w - a^K_w)/(a^L_r - a^K_r) > 1$ (eq. 3.20), **Results**: section 5.8

3. An increase in the cost of labour leads to labour-saving technical change or an increase in the cost of labour leads to capital-using technical change:
   Equation: $a^L_w > 0$ or $a^K_w < 0$ (eq. 3.20), **Results**: section 5.7

4. A relative increase in the cost of labour compared to the cost of capital leads to labour-saving technical change:
   Equation: $a^L_w > a^L_r$ (eq. 3.20), **Results**: section 5.8
   Equation: $a^L_{w/r} > 0$ (eq. 3.19), **Results**: appendix 3.E.2.[25]

Only the fourth interpretation corresponds exactly to the letter of Hicks's statement, but all correspond to the spirit of it. The fourth interpretation is to determine the relative determinant of labour-saving progress: which increase in r or in w is more correlated with λ_L. The first interpretation is more about the consequences of an increase in one price:

[25] We present the estimation of (3.19) in the appendices and only discuss it briefly in the main text.

whether an increase in wages triggers more labour-saving than capital-saving technical change.

The results are summarised in section 5.9 to provide an overview on Hicks's hypothesis.

5.2 Intrinsic bias & Endogeneity

To test Hicks's hypothesis, by either one of the previous interpretation of Hicks's statement, we regress the intensity of technical change on the evolution of prices. Nevertheless, two issues emerge. The first is the intrinsic bias of the framework. The second is the potential endogeneity of our specifications. We address these two issues in this section.

Intrinsic bias of the framework

The theoretical framework that we have developed is biased against the Hicks's hypothesis. If we regress the equations of the previous section, we will only reflect a mechanical influence of prices on the intensities of technical change λs through the factor shares that we use to compute the λs We offer an empirical strategy to overcome this bias in the next section 5.3.

The biased mechanism is the following: in a labour-intensive sector, an increase in the price of labour is correlated with net capital-saving technical change. In this situation, it will be all the more capital-saving as it is labour-intensive. Conversely, the labour-saving reaction to a rise in the price of labour does not depend on factor shares. This phenomenon directly contradicts Hicks's hypothesis.

Although mathematical and automatic, one could make sense of this relationship. If an industry had been able to do without an input (in this case labour), then it would have already developed the technologies that make it less dependent. If a hairdresser had solutions to do without labour, by automating either shampooing or cutting, they would probably already have resorted to it. The opposite explanation, which goes in the direction of Hicks, and which is our reference hypothesis for this section, is that a very labour-intensive sector will tend to save on labour if the price of labour rises.

Intrinsic bias in the model In the next paragraphs we prove the existence of an intrinsic bias baked into the framework: the relationship between prices and technical change intensities depends on the labour share of the industry. A price increase of the main input (input share superior to half) is correlated with technical-change savings on the other input. We state and prove the Lemma 3, and use it in Proposition 2.

Lemma 3 One of the interpretation of Hicks's hypothesis can be expressed as $\dfrac{\partial \lambda_L}{\partial w_1} > \dfrac{\partial \lambda_K}{\partial w_1}$. With all other parameters held constant, this expression can only be true for a specific range of wages.

Proof. With quantities and the cost of capital held constant, one can write:

$$\frac{\partial \lambda_L}{\partial w_1} = \frac{L_0}{Y_0 - r_1 K_0} \quad (3.21)$$

$$\frac{\partial \lambda_K}{\partial w_1} = \frac{r_1 L_0 K_0}{(Y_0 - w_1 L_0)^2}. \quad (3.22)$$

The following equation

$$\frac{\partial \lambda_L}{\partial w_1} - \frac{\partial \lambda_K}{\partial w_1} = \frac{L_0}{Y_0 - r_1 K_0} - \frac{r_1 L_0 K_0}{(Y_0 - w_1 L_0)^2} = 0 \quad (3.23)$$

has two roots:

$$w_m = \frac{Y_0}{L_0} - \sqrt{\frac{K_0 r_1 Y_0 - K_0^2 r_1^2}{L_0^2}} \quad (3.24)$$

$$w_M = \frac{Y_0}{L_0} + \sqrt{\frac{K_0 r_1 Y_0 - K_0^2 r_1^2}{L_0^2}}. \quad (3.25)$$

We then identify three domains of solutions;

- $\forall w_1 \in [0, w_m], \frac{\partial \lambda_L}{\partial w_1} < \frac{\partial \lambda_K}{\partial w_1}$
- $\forall w_1 \in [w_m, w_M], \frac{\partial \lambda_L}{\partial w_1} > \frac{\partial \lambda_K}{\partial w_1}$
- $\forall w_1 \in [w_M, +\infty], \frac{\partial \lambda_L}{\partial w_1} < \frac{\partial \lambda_K}{\partial w_1}$

□

Proposition 2. *Hicks's hypothesis expressed as* $\frac{\partial \lambda_L}{\partial w_1} < \frac{\partial \lambda_K}{\partial w_1}$ *holds if the economy or the industry is labour-intensive (with a labour-share higher than half).*

Proof. Suppose the cost of capital is constant over time, $r_1 = r_0$. In the economy or sector under consideration, the labour share is $\alpha_L = \frac{w_0 L_0}{Y_0} = \frac{1}{x}$ with $x >= 1$. Thus, we can write: $Y_0 = x w_0 L_0$ and $r_0 K_0 = Y_0 \frac{x-1}{x}$.

We can rewrite w_m and w_M, the roots of the equation (3.23) (Lemma 3), as functions of x:

$$w_m = w_0 \left(x - \sqrt{x-1} \right) \quad (3.26)$$

$$w_W = w_0 \left(x + \sqrt{x-1} \right) \quad (3.27)$$

Note that $\forall x > 1, w_0 \leq w_M$ and that $w_0 = w_m \leftrightarrow \alpha_L = 1$.

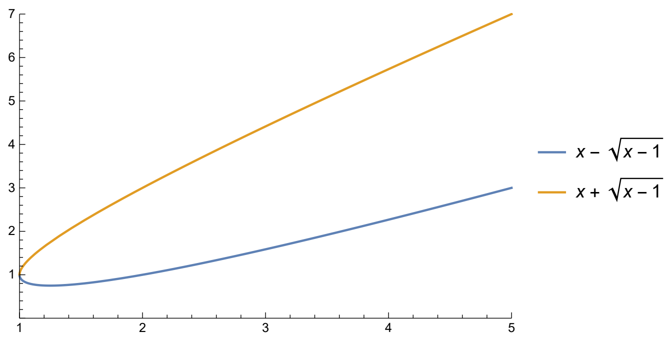
In a labour-intensive sector, $\alpha_L > 1/2$ and $x < 2$, and therefore $w_m < w_0$ (Fig.3.13) and $w_M > 2w_0$. If wage growth is not too large, which seems a reasonable assumption, then $w_1 \in [w_m, w_M]$, and thus $\frac{\partial \lambda_L}{\partial w_1} < \frac{\partial \lambda_K}{\partial w_1}$.

If $x > 2$, then the sector is capital-intensive, and $w_m > w_0$, then for a sufficiently low wage growth, $w_1 < w_m$ et $\frac{\partial \lambda_L}{\partial w_1} > \frac{\partial \lambda_K}{\partial w_1}$.

The relationship between $\frac{\partial \lambda_L}{\partial w_1}$ and $\frac{\partial \lambda_K}{\partial w_1}$ therefore depends on the share of factors.

□

Figure 3.13 – Roots of equation (3.23) against the inverse of the labour-share



Endogeneity

The second issue for the estimation of the induced technical change hypothesis is the endogeneity of technical change and prices. Technical change reacting to an increase in price limits the demand for the good that becomes too expensive, and therefore also acts as a mechanism to limit the price increase. When trying to estimate the impact of prices on the direction of technical change, one has to take into account this simultaneity bias symmetrical to the one that arises when estimating supply and demand curves in microeconomics.

At the industry level, one has good reasons to think there is little endogeneity as sectors as price-takers. The mobility of capital and labour across sectors means that the change in the demand of factors in the industry has little effect on its own sectoral prices, except if the workforce is captive because of the lack of other employment, because of specialised tasks or because the industry has a monopolistic behaviour.

5.3 Empirical strategy

The strategy for identifying induced technical change is to compare estimates of the directions of technical change λs by changes in input prices at the sectoral level of each country instrumented by aggregate input prices at the national level. Then compare these estimates to the results of the same estimations on randomly generated data.

The instrumentation allows us to capture only the direct effect of prices on technical change in each sector. It cancels the feedback effect of technical change on prices. The estimation of the relationship between technical change and prices on randomly generate gives a baseline of the mechanical bias of the framework for industries with similar factor shares.

Instrumentation

To deal with endogeneity, we instrument the prices of capital and labour inputs of each sector by the national prices of all sectors weighted by their shares in national GDP. We believe it is exogenous, because in small industries, technical change at the sectoral level is not likely to cause variations in wages and capital at the national level. At the same time, it is plausible that the level of wages in a particular sector is correlated with the general level of wages. Likewise, the capital cost for a sector, although specific to each sector risks and characteristics, depends on the aggregate demand and supply for capital. The variations of labour prices and the cost of capital at the national level constitute plausibly exogenous shocks to technical change at the sectoral level. Note that prices increase globally more for labour than for capital (see Figure 3.8).

We use standard two-stage least-squares estimation (2SLS). We test different instrumentations for each sector[26], including adding or removing a fixed effect in the estimation of the 1st or 2nd stage of the 2SLS. We test adding lagged national prices as instruments in the first step. Given the diversity of the industries we estimate for, we consider this search of the best instrumentation for each sector does not bias the results. The results we present still hold if we limit ourselves to the same specification and instrumentations for all sectors on all four databases.[27]

Randomly generated to overcome the framework bias

To quantify the intrinsic bias of the framework, we generate 20,000 fake time series. The price of capital r, the price of labour w and quantities of labour L and capital K are generated via a random walk of 33 periods (the number of periods in the U.S. series from 1986 to 2019) where the starting point is the result of a draw using a normal distribution $\mathcal{N}(1, 0.1)$, and each step is a draw using a normal distribution $\mathcal{N}(0, 0.05)$. Each of the 4 walks for each sector is completely independent. We compute the output as $Y = rK + wL$. We reject series where one of the prices or quantities becomes negative. A bias could arise from this selection but it is negligible over the large number of draws. We ensure that the factor shares follow a normal distribution.

We compute the metrics of technical change and regress the resulting λs on the randomly generated prices. We can be certain that there are no feedbacks from the λ on prices since the latter pre-exists the former.

5.4 Data & Method

We use the four datasets presented in section 3. The sectors corresponding to the economy as a whole are removed[28] since the instrumentation then loses all purpose.

Prices are considered in variation to take into account the fact that the λs are homogeneous to transformations between two points in time. In doing so we also correct

[26]In the case of the U.S., we test other national instruments that can influence factor prices without influencing sectoral technical change proposed by Young (2007, 2013). The proposed instruments are the growth rate of Treasury T-bills, the growth of the oil price, the growth of the money supply M1, the growth of government expenditure and the growth of the CPI. The final results of this instrumentation are not significant as the first step of the 2SLS is extremely weak.

[27]In this case, we adopt as first step the regression on national prices of capital and labour, without constant but with dummy outliers variables.

[28]"TOTAL INDUSTRIES" for KLEMS EU+ v2008 1970-2005; "Total — all NACE activities" for for KLEMS EU+ v2021 1997-2019 and KLEMS EU+ v2017 1997-2015.

the time trend of the price series and obtain stationary series. The λs series are naturally stationary.[29]

Prior to the estimation, we check each series for potential outliers. To that end, we use a basket of indicators[30] under the R package "performance". Observed λ_L, λ_K or λ_L/λ_K — depending on the variable of interest — are considered outliers if half of the methods of the basket describe them as outliers. Each outlier is then associated with an independent dummy variable that is used in the regression.

We consider only the estimates whose instrumentation is strong (F-statistics), consistent (Wu-Hausman test) and valid (Sargan overidentification test). We test the strength of the instruments using an F-test (standard threshold of 10) that the intruments are strongly correlated with the endogenous variable (Bound et al., 1995). The Wu-Hausman test allows us to test the null hypothesis that the OLS is at least as consistent as the IV. We keep only the estimates rejecting H_0 at the 5% threshold. The Sargan test tests the hypothesis that all the instruments are compatible. We do not include the industries rejecting this hypothesis at the 5% threshold.

5.5 Price variations on relative technical change

Estimated equation We estimate the coefficients $a_r^{L/K}$ and $a_w^{L/K}$ of equation (3.18), that we rewrite below:

$$\frac{\lambda_L}{\lambda_K} \sim \Delta w + \Delta r \iff \frac{\lambda_L}{\lambda_K} = a_w^{L/K}\Delta w + a_r^{L/K}\Delta r + \varepsilon.$$

Significance of the results The number of industries series with significant results for all these test is summarised in Table 3.3. About 13% of series have significant results in the four KLEMS databases. More than 60% of the randomly generated series have significant results. The difference might be due to the quality of the instrumentation or the correlation between labour and capital prices.

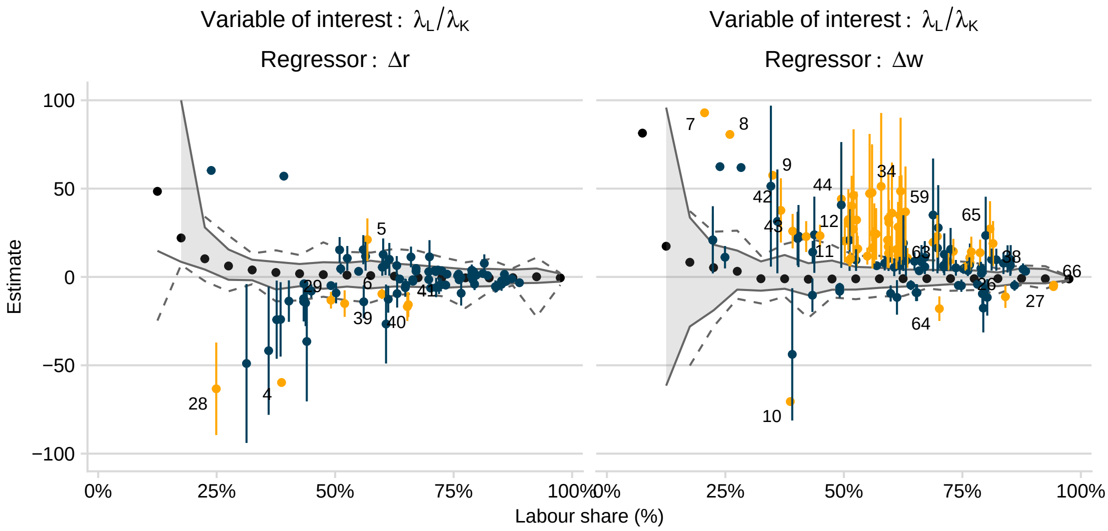
Table 3.3 – Presentation of the data and summary of the regression results for the estimation of the relationship between the relative intensity of technical change (λ_L/λ_K) and price variation ($\Delta w, \Delta r$)

	KLEMS EU+ v2008	KLEMS EU+ v2017	KLEMS EU+ v2021	KLEMS US v2021	Random
Number of series	801	478	747	83	20000
Series with strong instrumentation	311	146	185	24	—
Series with strong instrumentation and significative coefficients	89	36	136	12	13328

[29] Regressing on the differentiated or non-differentiated λ series does not change the conclusions.

[30] Namely, Cook's Distance, Pareto distribution tall shape, Median deviation from the mean, Median Absolute Deviation from the mean, Interquartile range vis-à-vis first and third quartile, Equal-Tailed Interval, Highest Density Interval, Bias Corrected and Accelerated Interval. See Lüdecke et al. (2021) for more details.

Figure 3.14 – Estimation of the relationship between the relative intensity of technical change (λ_L/λ_K) and price variation ($\Delta w, \Delta r$)



Note: The estimates are plotted against the sector's average share of work — real or randomly generated. The grey ribbon corresponds to the interval containing 90% of the estimates of the equation (3.18) over 20,000 randomly generated sectors. The dotted lines correspond to the interval at 95%. Black dots are the median of the estimates.
Each point corresponds to the estimate for a real sector from one of the four databases. Only the estimates for which the instruments are strong and the estimate for the 2nd step is significant are included. The error bars at 95% are added.
The colour of these dots is yellow when the 95% confidence intervals of the real sectors are disjoint from the 90% interval on randomised data. The numbered legends identifying the sectors highlighted in yellow correspond to the legends in Table 3.4.
Data: KLEMS US (1986-2019), KLEMS EU+ v2021 (1997-2019), KLEMS EU+ v2017 (1997-2015), KLEMS EU+ v2008 (1970-2005)

Results Figure 3.14 compares the estimates of the coefficients on real data (dots) and the estimates on randomly generated data for industries with similar labour shares.[31] The yellow dots are estimates whose 95% confidence interval are disjoint with the 90% confidence interval of the randomly data at that particular labour share.[32]

We find that the relative labour-saving technical change λ_L/λ_K increases with an increase in wages, and it is significantly more so on real data than on randomly generated data (Figure 3.14). On the contrary, λ_L/λ_K estimates are significantly negatively correlated with an increase in capital price.

[31] The x-axis is the average labour share of the industry (real or randomly generated) as Proposition 2 shows that the relationship depends on the share of labour.

[32] Considering both intervals at 90% does not exclude any points, so we have chosen to retain the more demanding criterion. Considering both intervals at 95% gives similar results for a smaller number of sectors.

An increase in wages is correlated with a net labour-saving technical change, while an increase in capital cost is correlated with a net labour-using technical change, that is, capital-saving. We conclude that firms innovate to save on the income becoming more expensive. Hence, it validates Hicks's hypothesis.

Salient industries 59 industries show a significant "Hicksian" effect of wages on the relative labour-saving technical change ($a_w^{\lambda_L/\lambda_K}$): the estimates are significantly more positive than the estimates on randomly generated data. They represent 46.4% of the estimates $a_w^{\lambda_L/\lambda_K}$ that the various significance tests. 12.8% of the estimates of $a_r^{\lambda_L/\lambda_K}$, that is 11 industries, are significantly more negative than the estimates on random data. Overall, the salient sectors are mostly manufacturing and industrial sectors (including Chemical industries, rubber & plastic, mineral exploitation, utilities, machinery, wood, etc) in Western European countries, with the noticeable exception of the Finance sector in Germany, in Italy and in the U.S. (Table 3.4).

5.6 Relative price variations effect on relative technical change

Estimated equation We estimate the coefficient $a_{w/r}^{L/K}$ of equation (3.17), that we rewrite below:

$$\frac{\lambda_L}{\lambda_K} \sim \Delta\frac{w}{r} \Longleftrightarrow \frac{\lambda_L}{\lambda_K} = a_{w/r}^{L/K}\Delta\left(\frac{w}{r}\right) + \varepsilon.$$

Significance of the results Only a few estimates have a strong instrumentation and significant estimation of the estimate.

Results The results are consistent with previous findings and Hicks's hypothesis. A relative increase in wages is correlated with net labour-saving technical change.

Salient industries Seven industries show estimates significantly more positive than randomly generated data (Figure 3.15). They represent 19.4% of all significant estimates. These industries are detailed in table 3.5. Utility sector in Japan and Sweden are capital-intensive (about 75%) and show a strong reaction to an increase in wages. Conversely, public administration in the U.S. shows smaller reaction, although significantly more positive than random data.

5.7 Price variations effect on technical change

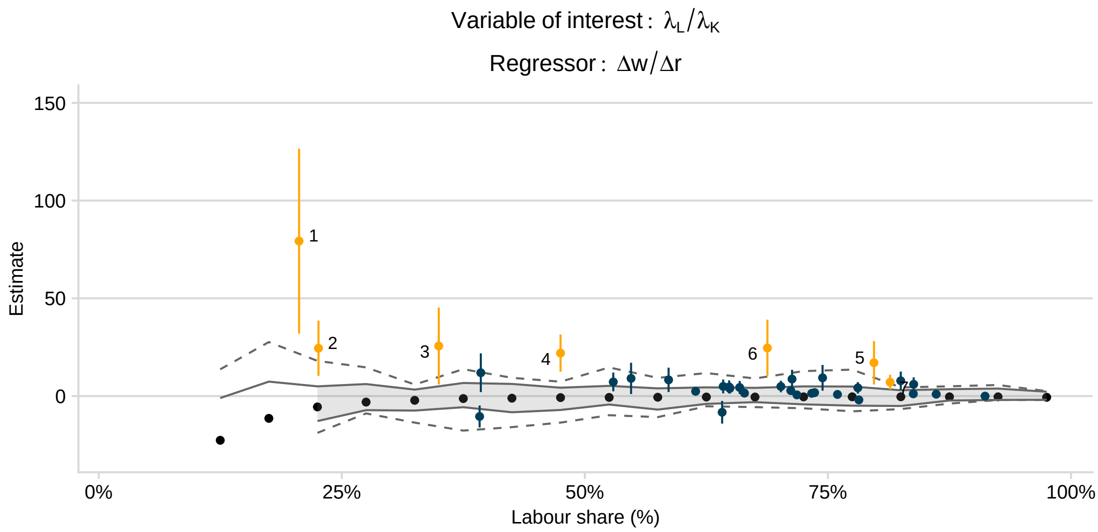
Estimated equation We estimate the coefficient a_w^L, a_r^L, a_w^K and a_r^K of equation 3.20, that we rewrite below:

$$\begin{aligned} \lambda_L \sim \Delta w + \Delta r \Longleftrightarrow \quad \lambda_L &= a_w^L \Delta w + a_r^L \Delta r + \varepsilon \\ \lambda_K \sim \Delta w + \Delta r \Longleftrightarrow \quad \lambda_K &= a_w^K \Delta w + a_r^K \Delta r + \varepsilon, \end{aligned}$$

Table 3.4 – Industries for which the relationship between the net direction of technical change (λ_L/λ_K) on prices variations ($\Delta w + \Delta r$) is significantly different from the relationship estimated on randomly generated series

Legend	Scope	Country	Industry code	Industry
1	KLEMS EU+ v2008	Australia	70	Real estate activities
2	KLEMS EU+ v2008	Germany	K	Real estate, renting and business activities
3	KLEMS EU+ v2008	Germany	JtK	Finance, insurance, real estate and business services
4	KLEMS EU+ v2008	Italy	JtK	Finance, insurance, real estate and business services
5	KLEMS EU+ v2008	Finland	I	Transport and storage and communication
6	KLEMS EU+ v2008	Portugal	71t74	Renting of m&eq and other business activities
7	KLEMS EU+ v2008	Japan	E	Electricity, gas and water supply
8	KLEMS EU+ v2008	Germany	K	Real estate, renting and business activities
9	KLEMS EU+ v2008	Japan	23t25	Chemical, rubber, plastics and fuel
10	KLEMS EU+ v2008	Italy	JtK	Finance, insurance, real estate and business services
11	KLEMS EU+ v2008	Czech Republic	I	Transport and storage and communication
12	KLEMS EU+ v2008	Czech Republic	60t63	Transport and storage
13	KLEMS EU+ v2008	Czech Republic	26	Other non-metallic mineral
14	KLEMS EU+ v2008	Sweden	64	Post and telecommunications
15	KLEMS EU+ v2008	Finland	60t63	Transport and storage
16	KLEMS EU+ v2008	Finland	I	Transport and storage and communication
17	KLEMS EU+ v2008	Japan	26	Other non-metallic mineral
18	KLEMS EU+ v2008	Japan	30t33	Electrical and optical equipment
19	KLEMS EU+ v2008	Sweden	15t16	Food , beverages and tobacco
20	KLEMS EU+ v2008	Germany	25	Rubber and plastics
21	KLEMS EU+ v2008	Germany	26	Other non-metallic mineral
22	KLEMS EU+ v2008	Sweden	AtB	Agriculture, hunting, forestry and fishing
23	KLEMS EU+ v2008	France	29	Machinery, nec
24	KLEMS EU+ v2008	Austria	30t33	Electrical and optical equipment
25	KLEMS EU+ v2008	Netherlands	G	Wholesale and retail trade
26	KLEMS EU+ v2008	Denmark	LtQ	Community social and personal services
27	KLEMS EU+ v2008	France	M	Education
28	KLEMS EU+ v2017	Italy	61	Telecommunications
29	KLEMS EU+ v2017	Czech Republic	10-12	Food products, beverages and tobacco
30	KLEMS EU+ v2017	United States	46	Wholesale trade, except of motor vehicles and motorcycles
31	KLEMS EU+ v2017	Slovak Republic	26-27	Electrical and optical equipment
32	KLEMS EU+ v2017	United States	J	Information and communication
33	KLEMS EU+ v2017	United States	G	Wholesale and retail trade; repair of motor vehicles and motorcycles
34	KLEMS EU+ v2017	Germany	58-60	Publishing, audiovisual and broadcasting activities
35	KLEMS EU+ v2017	United States	47	Retail trade, except of motor vehicles and motorcycles
36	KLEMS EU+ v2017	Sweden	31-33	Other manufacturing; repair and installation of machinery and equipment
37	KLEMS EU+ v2017	France	13-15	Textiles, wearing apparel, leather and related prodcuts
38	KLEMS EU+ v2017	Germany	O	Public administration and defence; compulsory social security
39	KLEMS EU+ v2021	France	C26	Manufacture of computer, electronic and optical products
40	KLEMS EU+ v2021	Spain	MARKT	Market economy (all industries excluding L, O, P, Q, T and U)
41	KLEMS EU+ v2021	Spain	MARKTxAG	Non-agricultural market economy (Market economy less industry A)
42	KLEMS EU+ v2021	EU12	J61	Telecommunications
43	KLEMS EU+ v2021	Czechia	C26	Manufacture of computer, electronic and optical products
44	KLEMS EU+ v2021	Austria	C29-C30	Manufacture of motor vehicles, trailers, semi-trailers and of other transport equipment
45	KLEMS EU+ v2021	Italy	J	Information and communication
46	KLEMS EU+ v2021	Austria	C26	Manufacture of computer, electronic and optical products
47	KLEMS EU+ v2021	France	C26	Manufacture of computer, electronic and optical products
48	KLEMS EU+ v2021	Belgium	J	Information and communication
49	KLEMS EU+ v2021	Austria	C26-C27	Computer, electronic, optical products; electrical equipment
50	KLEMS EU+ v2021	Czechia	C26-C27	Computer, electronic, optical products; electrical equipment
51	KLEMS EU+ v2021	Finland	C16-C18	Manufacture of wood, paper, printing and reproduction
52	KLEMS EU+ v2021	France	C26-C27	Computer, electronic, optical products; electrical equipment
53	KLEMS EU+ v2021	Finland	H52	Warehousing and support activities for transportation
54	KLEMS EU+ v2021	Estonia	TOT_IND	Total industries (A-S)
55	KLEMS EU+ v2021	Austria	C16-C18	Manufacture of wood, paper, printing and reproduction
56	KLEMS EU+ v2021	Finland	J	Information and communication
57	KLEMS EU+ v2021	Estonia	MARKT	Market economy (all industries excluding L, O, P, Q, T and U)
58	KLEMS EU+ v2021	Netherlands	J	Information and communication
59	KLEMS EU+ v2021	Austria	C22-C23	Manufacture of rubber and plastic products and other non-metallic mineral products
60	KLEMS EU+ v2021	Austria	C28	Manufacture of machinery and equipment n.e.c.
61	KLEMS EU+ v2021	Austria	I	Accommodation and food service activities
62	KLEMS EU+ v2021	Czechia	C27	Manufacture of electrical equipment
63	KLEMS EU+ v2021	Austria	K	Financial and insurance activities
64	KLEMS EU+ v2021	Spain	C16-C18	Manufacture of wood, paper, printing and reproduction
65	KLEMS EU+ v2021	Austria	O	Public administration and defence; compulsory social security
66	KLEMS EU+ v2021	Finland	Q	Human health and social work activities
67	KLEMS US v2021	United-States	711712	Performing arts, spectator sports, museums, and related activities
68	KLEMS US v2021	United-States	71	Arts, entertainment, and recreation
69	KLEMS US v2021	United-States	52	Finance and insurance
70	KLEMS US v2021	United-States	71-72	Arts, entertainment, recreation, accommodation, and food services

Figure 3.15 – Estimation of the relationship between the relative intensity of technical change (λ_L/λ_K) and relative price variation ($\Delta w/r$). Sample: KLEMS EU, 1970-2005, 1996-2019.



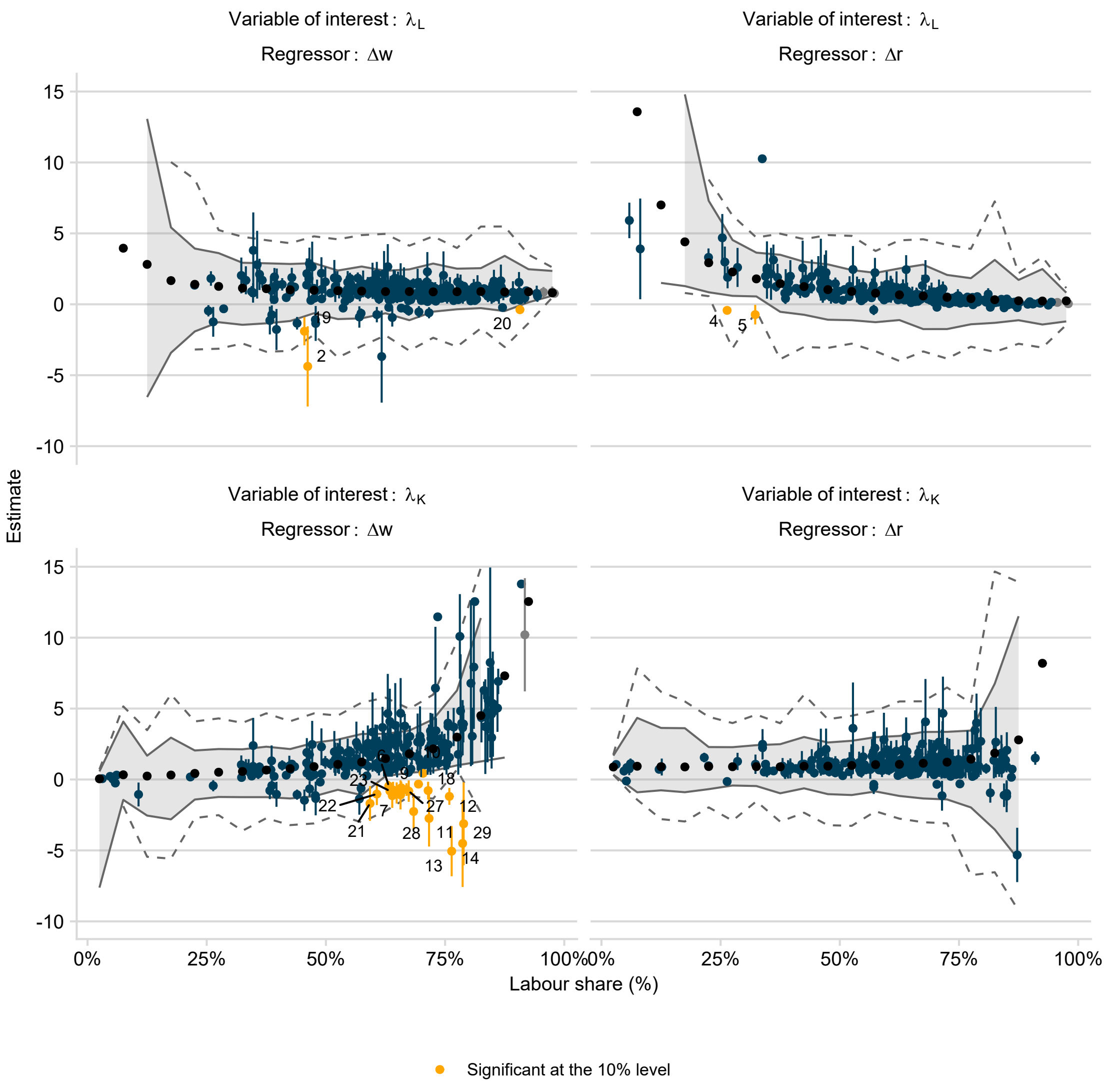
Note: See note Figure 3.14. The numbered legends identifying the sectors highlighted in yellow correspond to the legends in Table 3.5.

Table 3.5 – Industries for which the relationship between the net direction of technical change (λ_L/λ_K) on relative prices variations ($\Delta w/r$) is significantly different from the relationship estimated on randomly generated series. Sample: KLEMS EU, 1970-2005, 1996-2019, 1997-2015.

Legend	Scope	Country	Industry code	Industry
1	KLEMS EU+ v2008	Japan	E	Electricity, gas and water supply
2	KLEMS EU+ v2008	Sweden	E	Electricity, gas and water supply
3	KLEMS EU+ v2008	Japan	23t25	Chemical, rubber, plastics and fuel
4	KLEMS EU+ v2017	Italy	J	Information and communication
5	KLEMS EU+ v2017	United States	O	Public administration and defence; compulsory social security
6	KLEMS EU+ v2021	Netherlands	O	Public administration and defence; compulsory social security
7	KLEMS EU+ v2021	Austria	Q	Human health and social work activities

Significance of the results The instrumentation and estimation results for equation are described in Table 3.6. It comes that almost half of the industries do not pass the test of a robust instrumentation (Weak instruments test, Wu-Hausman and Sargan test) and the significance of both regressors at 5% for the 1st step of 2LSL. Half of the series with strong instruments do not give significant results in the second step of the estimation (at the 5% threshold).
A selection of regression tables is available in appendix 3.E.3.

Figure 3.16 – Estimation of the relationship between the intensity of technical change ($\lambda_{(K,L)}$) and price variation ($\Delta w, \Delta r$)



Note: The point estimates are plotted against the sector's average share of work — real or randomly generated.
The grey ribbon corresponds to the interval containing 90% of the estimates of the equation (3.20) over 20,000 randomly generated sectors. The dotted lines correspond to the interval at 95%. Black dots are the median of the estimates.
Each point corresponds to the estimate for a real sector from one of the three databases. Only the estimates for which the instruments are strong and the estimate for the 2nd step is significant are included. The error bars at 95% are added.
The colour of these dots is yellow when the 95% confidence intervals of the real sectors are disjoint from the 90% interval on randomised data. The numbered legends identifying the sectors highlighted in yellow correspond to the legends in the table 3.7.
Data: KLEMS US (1986-2019), KLEMS EU+ v2021 (1997-2019), KLEMS EU+ v2017 (1997-2015), KLEMS EU+ v2008 (1970-2005)

Table 3.6 – Presentation of the data and summary of the regression results for the estimation of the relationship between the intensity of technical change ($\lambda_{(K,L)}$) and price variation ($\Delta w, \Delta r$)

	KLEMS EU+ v2008	KLEMS EU+ v2017	KLEMS EU+ v2021	KLEMS US v2021	Random
Number of series	801	478	747	83	20000
Series with strong instrumentation	482	189	281	52	
Series with strong instrumentation and significative coefficients	231	93	136	46	19100

Results We find no points significantly different from the randomly generated data for the coefficient a_r^K. Three estimates of a_w^L are significantly more negative than estimates on randomly generated data. These estimates contradict Hicks's hypothesis since an increase in labour costs is associated with an increased labour-using technical change.

However, we find significantly negative values for the estimates of a_w^K, representing the relationship of Δw on λ_K, i.e. an increase in wages is correlated with capital-using, thus labour-saving technical change. This effect is in line with Hicks's hypothesis.

A few industries have significantly negative coefficients between Δr and λ_L (a_r^L), i.e. an increase in the cost of capital is correlated with labour-using, thus capital-saving technical change. These observations, although sparse, are also in line with Hicks's hypothesis.

In randomly generated data, a_w^L (relationship between Δw and λ_L) and a_r^K (relationship between Δr and λ_K) are not significantly positive or negative, but it appears that an overwhelming majority of the coefficients estimated on real sectors are positive (90.7%). This effect is of small significance but in line with Hicks's hypothesis.

Salient industries 30 industries (Table 3.7) have estimates of a_w^K significantly more negative than the estimates on randomly generated data. These industries account for 9.5% of the significant (strong instrumentation and significant second step coefficients) estimates for a_w^K. They are from the three European databases. A large part of them are manufacturing and heavy manufacturing industries, transport and storage and the food industry.[33] The industries and countries represented are sufficiently varied to ensure that our results are not due to a single systematic bias.

5.8 Alternative estimate of the (relative) price variations effect on (relative) technical change

We can use the coefficients of the equation (3.20) to estimate the effects of a relative increase in price on technical change intensities (as in eq. (3.19), appendix 3.E.2) or the

[33] Note that the manufacturing sectors are less sensitive to errors in the measurement of labour and capital flows than the services for example. It does add to the level of confidence to be given to these results.

Table 3.7 – Industries for which the relationship between the intensity of technical change ($\lambda_{(K,L)}$) and price variations ($\Delta w, \Delta r$) is significantly different from the relationship estimated on randomly generated series

Legend	Scope	Country	Industry code	Industry
1	KLEMS EU+ v2008	Denmark	C	Mining and quarrying
2	KLEMS EU+ v2008	Slovenia	K	Real estate, renting and business activities
3	KLEMS EU+ v2008	Denmark	C	Mining and quarrying
4	KLEMS EU+ v2008	Japan	K	Real estate, renting and business activities
5	KLEMS EU+ v2008	US	E	Electricity, gas and water supply
6	KLEMS EU+ v2008	Luxembourg	D	Total manufacturing
7	KLEMS EU+ v2008	Portugal	15t16	Food , beverages and tobacco
8	KLEMS EU+ v2008	Finland	25	Rubber and plastics
9	KLEMS EU+ v2008	France	15t16	Food , beverages and tobacco
10	KLEMS EU+ v2008	Portugal	I	Transport and storage and communication
11	KLEMS EU+ v2008	Austria	15t16	Food , beverages and tobacco
12	KLEMS EU+ v2008	Austria	29	Machinery, nec
13	KLEMS EU+ v2008	United Kingdom	26	Other non-metallic mineral
14	KLEMS EU+ v2008	Austria	25	Rubber and plastics
15	KLEMS EU+ v2008	Netherlands	50	Sale, maintenance and repair of motor vehicles and motorcycles; retail sale of fuel
16	KLEMS EU+ v2008	Finland	AtB	Agriculture, hunting, forestry and fishing
17	KLEMS EU+ v2017	Netherlands	H	Transportation and storage
18	KLEMS EU+ v2017	Czech Republic	47	Retail trade, except of motor vehicles and motorcycles
19	KLEMS EU+ v2021	EU12 without UK	C20-C21	Chemicals; basic pharmaceutical products
20	KLEMS EU+ v2021	Germany	C31-C33	Manufacture of furniture; jewellery, musical instruments, toys; repair and installation of machinery and equipment
21	KLEMS EU+ v2021	Germany	C26	Manufacture of computer, electronic and optical products
22	KLEMS EU+ v2021	Germany	J	Information and communication
23	KLEMS EU+ v2021	Germany	C29-C30	Manufacture of motor vehicles, trailers, semi-trailers and of other transport equipment
24	KLEMS EU+ v2021	Germany	C26-C27	Computer, electronic, optical products; electrical equipment
25	KLEMS EU+ v2021	EU12 without UK	C	Manufacturing
26	KLEMS EU+ v2021	Italy	C	Manufacturing
27	KLEMS EU+ v2021	Italy	C16-C18	Manufacture of wood, paper, printing and reproduction
28	KLEMS EU+ v2021	Germany	H	Transportation and storage
29	KLEMS EU+ v2021	Germany	C24-C25	Manufacture of basic metals and fabricated metal products, except machinery and equipment
30	KLEMS US v2021	United-States	62	Health care and social assistance

Note: 5 points (1, 3, 15, 16, 30) are displayed in this table but not in the associated figure 3.16. Including them would make the graph difficult to read. For an analysis of these points see the appendix 3.E.14 and figure 3.E.14.

effect of an increase in price on the relative technical change (as in eq. (3.18), section 5.5).

First, we study the difference between the coefficients $a_w^L - a_r^L$ (resp $a_w^K - a_r^K$), that is the relative response in labour-saving (resp capital-saving) faced with a similar increase in labour and capital prices. For both randomly generated data and KLEMS data we consider the difference between the coefficients as significant if their 95% confidence intervals are completely disjoint. Figure 3.17 shows the density of $a_w^L - a_r^L$ (left) and $a_w^K - a_r^K$ (right) when the difference between the two coefficients is significant. The grey distribution is the distribution of the randomly generated data. Green points indicate the gap between coefficients estimated on KLEMS database.[34]

For a number of real industries, the difference between the coefficients is significantly different from the one predicted by the randomly generated data (Figure 3.17).[35]

[34]Hence the two-peak shape around 0, since a gap of 0 is qualified by two coefficients not statistically different from each other.

[35]For randomly generated data, the difference between the impacts of labour and capital cost on λ_L (left panel)is negative for the capital-intensive sectors. That is, an increase in the cost of capital is correlated with a more labour-saving technical change than an equivalent increase in the cost of labour. And for labour-intensive sectors, the labour-saving response to wage increases is greater than that to capital cost increases.

This difference is more negative than expected for labour-intensive industries. This contradicts Hicks's hypothesis: the labour-saving technical change is more correlated to an increase in the cost of capital than of labour.

Conversely, the difference between the impacts of labour and capital cost on λ_K (right panel) shows some labour-intensive industries where the difference is more negative than expected. That is to say, λ_K is correlated to Δr rather than to Δw.[36] This effect is in line with Hick's hypothesis.

Secondly, we study the difference between the coefficients $a_w^L - a_w^K$ (resp. $a_r^L - a_r^K$). That is, the intensity in both directions of technical change when faced with an increase in labour cost (resp. capital cost). For some rare industries the difference between the coefficients is more positive than the randomly generated data estimate (Figure 3.18) for both $a_w^L - a_w^K$ (left panel) and $a_r^L - a_r^K$ (right panel). That is, an increase in labour costs is correlated with a greater reaction in capital-saving than in labour-saving. This effect contradicts Hicks's hypothesis. But conversely, an increase in the cost of capital causes a net capital-saving response as expected by Hicks's hypothesis.

5.9 Insights on Hicks's hypothesis

To summarise the results of this section: estimates of the relationship between the intensity of labour-saving and capital-saving technical change and price changes yield significant results. We have mixed evidence, but the most significant results seem to confirm Hicks' hypothesis of induced technical change to save on the (relatively) more expensive input.

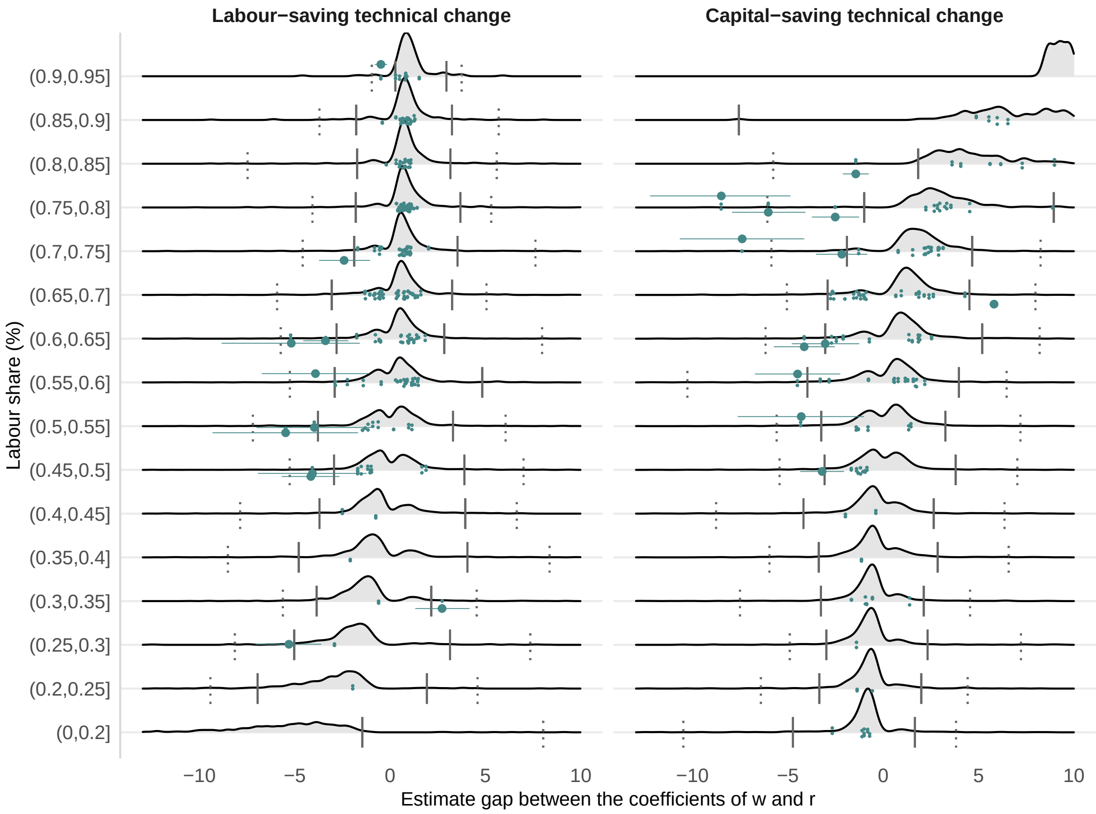
We have proceeded in two steps to lift the simultaneity issue and estimate the causality between price increases and technical change. The first step is the instrumentation of price changes. It allows us to eliminate the feedback effect of technical change, which would tend to moderate price changes. The second step compares our estimates with those obtained from randomly generated data. By construction, the randomly generated data cannot encompass feedback effects from technical change on prices or economic insights, all relationships being derived from the framework hypotheses. The comparison isolates the contribution of the framework itself to the relationships we are trying to estimate between prices and technical change. The instrumentation of prices makes the estimations causal.

Some of the estimates are significantly different from the estimates on the randomised data. It leads us to conclude that some induced innovation effects are taking place.

In more detail, we find several effects in line with Hicks's hypothesis (we indicate when the observed effect is sparse and thus less reliable than other results). We find that for most of sector — which have a robust estimate — the labour bias of technical change, that is the relative labour-saving technical change (λ_L/λ_K), increases with the price of labour. The same quantity decreases with the cost of capital. We also find that capital-using technical change increases with labour price; and labour-using technical change

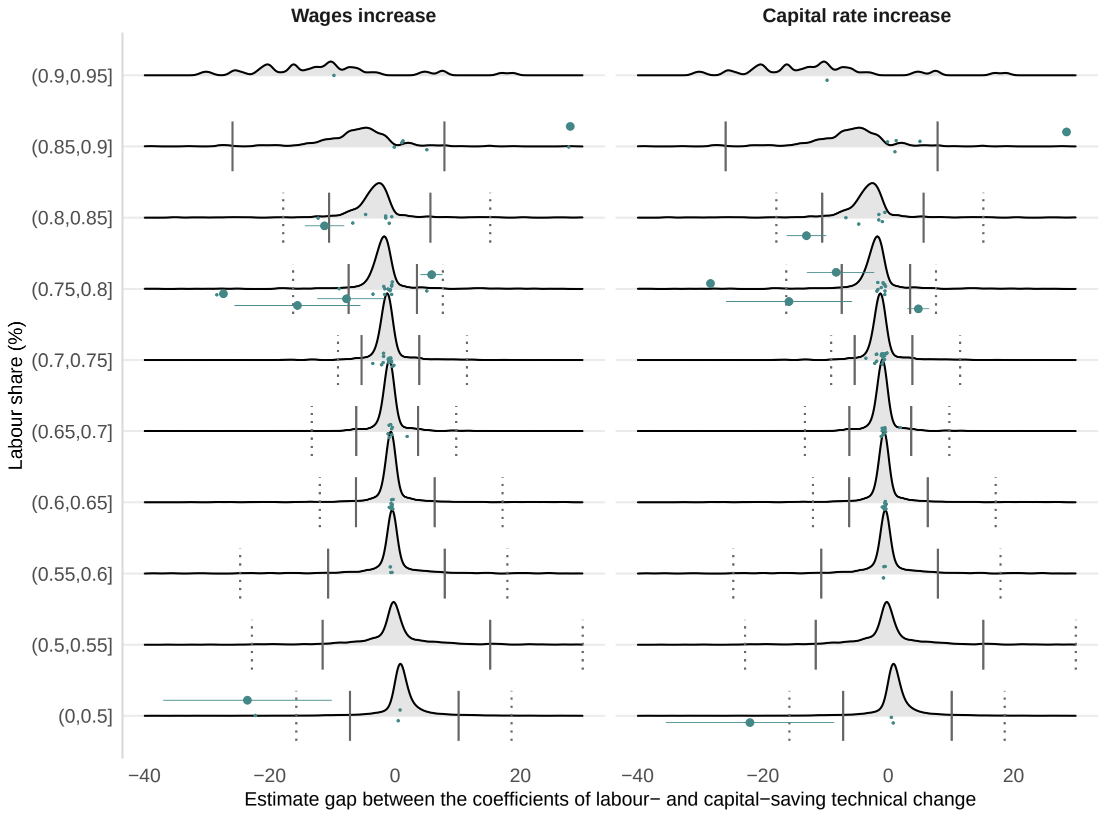
[36] $\lambda_K \sim (\Delta w - \Delta r)$ shows a negative correlation. Thus the reaction in r is greater than that in w.

Figure 3.17 – Gap between the coefficients of price changes $(\Delta w, \Delta r)$ for each direction of technical change$(\lambda_{(K,L)})$



Note: The points and distribution represent gap between estimates of the equation (3.19). Respectively the quantities plotted are $a_w^L - a_r^L$ (left) and $a_w^K - a_r^K$ (right). Estimates are split according to the industry average share of labour — real or random. The grey distribution is the distribution of the randomly generated data. Confidence intervals at 90% are indicated in plain black lines, intervals at 95% are indicated in dotted black line. Green points indicate the difference between coefficients estimated on KLEMS database. 95% intervals are added on the graph only when the estimate is outside of the randomly generated data 90% confidence interval. Data: KLEMS US (1986-2019), KLEMS EU+ v2021 (1997-2019), KLEMS EU+ v2017 (1997-2015), KLEMS EU+ v2008 (1970-2005)

Figure 3.18 – Gap between the coefficients of technical change direction changes ($\lambda_{(K,L)}$) for changes in each factor price($\Delta w, \Delta r$)



Note: The points and distribution represent gap between estimates of the equation (3.19). Respectively the quantities plotted are $a_w^L - a_w^K$ (left) and $a_r^L - a_r^K$ (right). Estimates are split according to the industry average share of labour — real or random. The grey distribution is the distribution of the randomly generated data. Confidence intervals at 90% are indicated in plain black lines, intervals at 95% are indicated in dotted black line. Green points indicate the gap between coefficients estimated on KLEMS database. 95% intervals are added on the graph only when the estimate is outside of the randomly generated data 90% confidence interval. Data: KLEMS US (1986-2019), KLEMS EU+ v2021 (1997-2019), KLEMS EU+ v2017 (1997-2015), KLEMS EU+ v2008 (1970-2005) increases with capital price (sparse). We find that capital-saving technical change reacts to the price of capital rather than to the price of labour (sparse), and that an increase in the price of capital triggers a net capital-saving response (sparse).

However, we also point out effects that contradict Hicks's hypothesis. For some industries, that labour-saving technical change decreases with labour prices (sparse); that labour-saving technical change reacts to the price of capital rather than the price of labour (sparse); and that an increase in the price of labour is associated with a net capital-saving technical change (sparse).

We also find insignificant results: there is no relationship significantly different from randomly generated data for the cost of capital and capital-saving technical change.

When significant effects arise, they take place in various industries and countries. Hence, the effects are not due to a systemic bias of the data of a specific country or industry. We highlight a large heterogeneity in the responses to price increases across industries

The industries and countries represented are sufficiently varied to ensure that our results are not due to a single systematic bias. The data we handle are subject to many biases and measurement errors, for example the valuation of capital service flows. We have used different databases with different levels of detail and methodologies, so we have introduced additional noise. Under these conditions, the effects we obtain are remarkably clear and show price-induced technical change.

6 Forecasting factor shares

In this section, we forecast the labour share dynamics in each industry. One of the major contributions of this chapter is to build indicators of technical change bias that take into account the factor. Classical models of growth accounting, such as Solow's, in addition to not being able to decompose the directions of technical change and capital deepening, also assume fixed factor shares.

Our forecast of the labour share serves two purposes: to offer another practical application of our framework and to check the validity of our framework by comparing it to a selection of other production functions.

An advantage of our framework is that it is easy to forecast the factor share and bias of technical change. Indicators of technical change can be constructed from one year to the next and thus the dynamics of technical change can be estimated stepwise, which makes it particularly easy to incorporate into all kinds of economic projection models. Unlike CES functions, the whole dynamic of our framework does not rely on the estimation of one single elasticity of substitution between capital and labour.

6.1 Basic principles

Our framework, hereafter "Convex hull production function" in the figures and tables, would be validated if it significantly improved the forecast of factor shares compared to three other specifications:

- **Cobb-Douglas** hypothesis of constant factor share,
- **Leontief** with null elasticity of substitution and constant intensities in capital and labour,
- **CES**, constant elasticity of substitution, function with trend-like total factor productivity.

We use KLEMS US data on 81 sectors or aggregates of sectors (which partially overlap). Using a single database allows us to have series of identical sizes (33 years) and similar construction, which simplifies inter-sector and inter-model comparisons.

The principle is to split the data set between a training set of data and a testing set where we use the previously calibrated model to forecast factor share assuming perfect knowledge of the prices of labour, output and capital. We use a standard split of 80%/20% between the training and the testing set.[37] That is, out of 33 years available, we use the data 1987-2012 for the training set, and leave 2013-2019 for the testing set.

We first detail how we train the 4 models on the training set, then compare the results.

6.2 Training set — building the estimators

Framework

Both λs can be computed using current period price — which are given in the testing set. To compute quantities of input K and L and output Y, we need to compute the βs, which are the allocation of inputs to each factor-saving function.

We estimate three functional forms for the β. We add to each specification dummy variables to signal outliers. We suppose either:

- an auto-regressive process, where β follow a time-trend;

$$\begin{aligned} \beta_L(t) &= \alpha_0 + \alpha_1 \beta_L(t-1) + \alpha_2 \beta_K(t-1) + \varepsilon \\ \beta_K(t) &= \alpha'_0 + \alpha'_1 \beta_L(t-1) + \alpha'_2 \beta_K(t-1) + \varepsilon \end{aligned} \tag{3.28}$$

- Or that the allocation depends only on the intensity and direction of technical change

$$\begin{aligned} \beta_L(t) &= \alpha_0 + \alpha_1 \lambda_L(t) + \alpha_2 \lambda_K(t) + \varepsilon \\ \beta_K(t) &= \alpha'_0 + \alpha_1 \lambda_L(t) + \alpha_2 \lambda_K(t) + \varepsilon \end{aligned} \tag{3.29}$$

- Or that the allocation depends both on past allocation and the intensity and direction of technical change

$$\begin{aligned} \beta_L(t) &= \alpha_0 + \alpha_1 \beta_L(t-1) + \alpha_2 \beta_K(t-1) + \alpha_3 \lambda_L(t) + \alpha_4 \lambda_K(t) + \varepsilon \\ \beta_K(t) &= \alpha'_0 + \alpha'_1 \beta_L(t-1) + \alpha'_2 \beta_K(t-1) + \alpha_3 \lambda_L(t) + \alpha_4 \lambda_K(t) + \varepsilon \end{aligned} \tag{3.30}$$

[37] This assumption is relaxed in the course of the analysis.

Note that we do not constrain the sum of betas. Therefore, one should not look at the quantities of inputs, but only at the ratios of intensities of technical change, and thus at the share of factors.

Computation of the set of coefficients characterising our Framework "Convex Hull" then happens in 4 steps:

- **Step 1:** Compute the intensity of technical change (λ_K, λ_L):
  $\lambda_{K,L} = f(K_0, L_0, Y_0, r_1, w_1)$
- **Step 2:** Estimate the input allocation β_K, β_L using the λs computed in step 1 and the relationship estimated in equation (3.28), (3.29) or (3.30)
  $\beta_{K,L} = f(\lambda_K, \lambda_L, \beta_{K,L}(t-1))$
- **Step 3:** Compute the consumption of capital K_1 and labour L_1 at time $t = 1$
  $K_1, L_1 = f(\lambda_{K,L}, \beta_{K,L}, K_0, L_0, Y_0)$
- **Step 4:** Compute the output Y_1 and factor shares:
  $Y_1 = r_1 K_1 + w_1 L_1$, $\alpha_L = f(K_1, L_1, Y_1, r_1, w_1)$.

CES

We calibrate the CES function for each industry, in the form of

$$F(K,L) = A\left(bK^{\frac{\sigma-1}{\sigma}} + (1-b)L^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}. \tag{3.31}$$

We need to estimate three parameters: σ, the elasticity of substitution between capital and labour, b the distribution parameter, and A the total productivity factor.

We calibrate elasticity of substitution following Balistreri et al. (2003). We estimate at the industry level the following three specifications.

- If series are stationary, the short-term elasticity of substitution between capital and labour is β_1

$$\ln\left(\left(\frac{w}{r}\right)_t\right) = \beta_0 + \beta_1 \ln\left(\left(\frac{K}{L}\right)_t\right) + \beta_2 \ln\left(\left(\frac{w}{r}\right)_{t-1}\right) + \varepsilon. \tag{3.32}$$

- If the first-difference series are stationery ($I(1)$), the short-term elasticity of substitution between capital and labour is β_1

$$\Delta\ln\left(\left(\frac{w}{r}\right)_t\right) = \beta_0 + \beta_1 \Delta\ln\left(\left(\frac{K}{L}\right)_t\right) + \varepsilon. \tag{3.33}$$

- If the first-difference series are stationery ($I(1)$) but with cointegration, the short-term elasticity of substitution between capital and labour is β_1

$$\Delta\ln\left(\left(\frac{w}{r}\right)_t\right) = \beta_0 + \beta_1 \Delta\ln\left(\left(\frac{K}{L}\right)_t\right) + \beta_2 \ln\left(\left(\frac{w}{r}\right)_{t-1}\right) + \beta_3 \ln\left(\left(\frac{K}{L}\right)_{t-1}\right) + \varepsilon. \tag{3.34}$$

We follow Klump and de La Grandville (2000) to calibrate the distribution parameter, building on Rutherford (1995) normalisation:

$$b = \pi_0 \left(\frac{Y_0}{K_0}\right)^{\rho} A^{\rho} \tag{3.35}$$

with $A = \left(\pi_0 \left(\frac{Y_0}{K_0}\right)^{\rho} + (1-\pi_0)\left(\frac{Y_0}{L_0}\right)^{\rho}\right)^{1} / \rho$, the capital share $\pi_0 = r_0 K_0 / Y_0$, and $\rho = 1 - 1/\sigma$.

We make an extra assumption of exogenous technical change, and approximate the trend in TFP using a piecewise regression model (Lemire, 2007). This is in line with the recent work of Philippon (2022) who finds a linear TFP growth.

We also assume one single constant elasticity of substitution, since we use it for short-term forecast. Balistreri et al. (2003) estimates long- and short-term elasticities. Hicks discusses the fact that the elasticity of substitution can change under the constraint of technical change (Brugger and Gehrke, 2017), see for example the work of Brown and De Cani (1963).

Our sigma estimates are reported in the appendix 3.F, Figure 3.F.16. Our estimates are low, but plausible when compared to estimates in the literature.[38]

We are aware that the specification we use is not state of the art: see in particular the work of Antras (2004); León-Ledesma et al. (2010); Klump et al. (2007); Herrendorf et al. (2015). Klump et al. (2007) estimates a CES function and determines both the elasticity of substitution and the factor-augmenting parameters whose expression reveals the elasticity of substitution, and thus intertwines the two mechanisms. Herrendorf et al. (2015) use a system of equations to estimate the elasticity of substitution, Hicks-Neutral technical change and labour-augmenting technical change for 3 sectors (agriculture, manufacturing, services). They use a three-stage least squares method. This level of precision is intractable in the context of our study.

To take into account the advances in the field and other methods of estimating substitution elasticities, we use the elasticities estimated by Young (2013) on 35 U.S. sectors. It uses a CES function allowing for factor-augmenting technical change.[39]

Leontief and Cobb-Douglas

The Cobb-Douglas form for the production function comes with an hypothesis of fixed factor share.

The Leontief form supposes no technical change. Changes in factor share are mechanical

[38] One possible explanation may be that our sectors are very precisely defined (81). This is the hypothesis of Solow (1964, p. 118) who asserts that "[i]t seems plausible that, in general, elasticities of substitution should be smaller the more narrowly defined the industrial classification, and larger the degree of aggregation." cited in Young (2013). Although Young does not seem to find any empirical proof of it in his study.

[39] We use without discrimination the 8 estimates of the capital-labour elasticity of each sector, which are added to the 3 estimates following the method of Balistreri et al. (2003). We will then retain the model allowing the forecast with the lowest error.

adjustment to prices variations. We assume fixed quantity of capital and labour consumed for each industry,

$$\begin{aligned} Y_1 &= r_1 K_0 + w_1 L_0 \\ \alpha_K &= \frac{r_1 K_0}{Y_1} \\ \alpha_L &= \frac{w_1 L_0}{Y_1} \end{aligned} \tag{3.36}$$

6.3 Testing set — Comparing forecast

We test the predictive power of the four models calibrated on the training set (1987-2012) by feeding them the real prices for capital and labour, for each sector, of the testing set (2013-2019). We compare the forecast of the share of labour until 2019 to the true value. We use root-mean-squared percentage error (RMSPE) to choose the best forecast.[40] For each of the four models we retain the best specification in terms of error.

Figure 3.19 shows the forecast for 4 sectors, 3 of which are sectors that were the focus of the previous section, and another industrial sector — the paper industry. The results are remarkably good for our framework, but we should humbly note that the Leontief model also performs very well. Our framework is able to anticipate shocks to the labour share. These shocks are most likely price-related, since Leontief functions and our framework display the same ones. But the magnitude of these shocks are modulated by technical change. This is particularly visible in the forecasts for agriculture and manufacturing where our model is closer in level to the actual labour share than the Leontief model.

The specification chosen for our framework allows us to accurately anticipate variations in the labour share by reproducing the technical change bias (λ_L/λ_K) (see in appendix, figure 3.F.18).

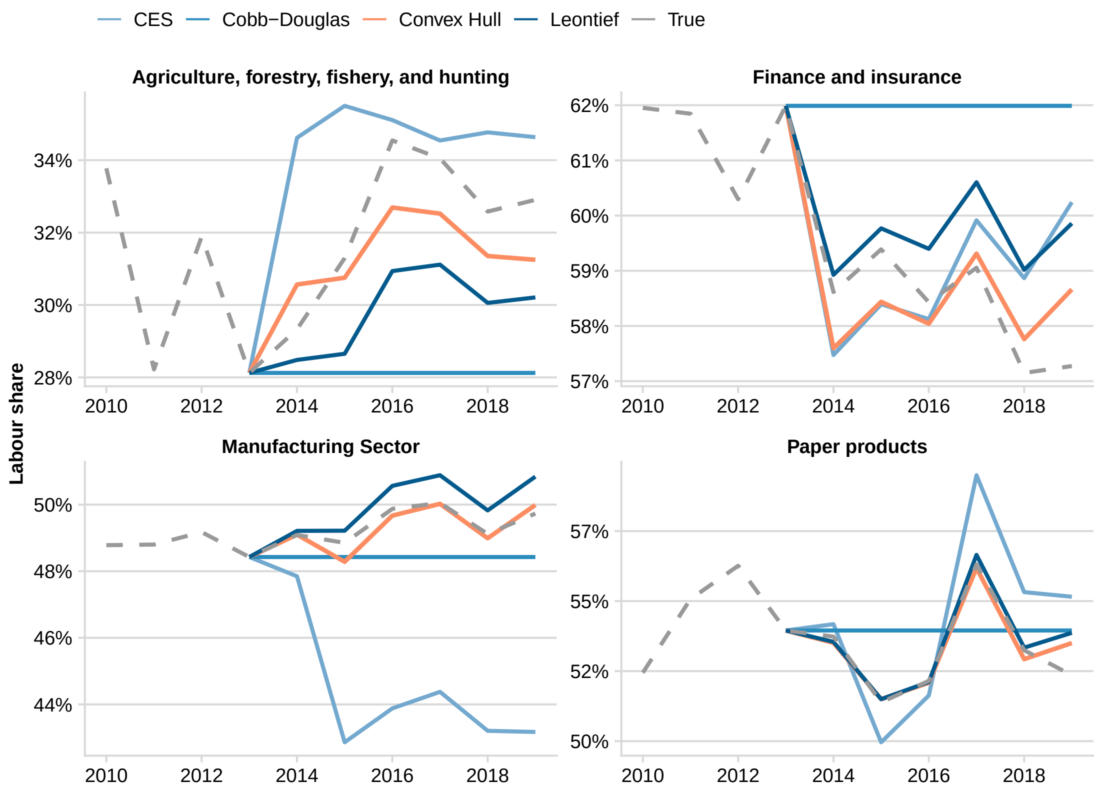
Table 3.8 shows the percentage of sectors (unweighted) for which each model provides the best forecast over the 2013-2019 period. Our framework "convex hull" receives the highest score compared to the other three models. We compare the forecast performance of models 1 against 1. Our model is the only one that performs better than any other model.

We compare the performance of the 4 models across all sectors and present the results in figure 3.20. The colours of the sector codes on the vertical axis indicate which is the best model. They reflect the numbers of Table 3.8. First result: in the cases where our model is not the most accurate, it still shows a very low aggregate error (less than 5% in aggregate) on almost all sectors. This is not the case with other models, which sometimes perform better and sometimes very poorly. Our framework offers a very poor forecast for 6 sectors located at the bottom of the graph with an error higher than 5% on average.[41] For 4 of them, the other models also have an average error of 5%,

[40] We test other indicators of goodness of fit: root-mean-squared absolute error (RMPE), Mean absolute Error (MAE), Mean Absolute percentage error (MAPE), without significant change.

[41] 512, 211, 481, 324, 518519, 525, see appendix, table 3.C.1.

Figure 3.19 – Forecast of labour share using our framework vs the true value (grey) and the 3 other models



Note: For each model we retain the specification allowing the forecast with the lowest error (RMSE).

Table 3.8 – Comparing the four models predictive power

	CES	Cobb-Douglas	Convex Hull	Leontief
Comparing the four models predictive power				
Best model	26%	11%	36%	27%
Comparing one model predictive power (line) to another (row)				
CES	100%	53%	63%	63%
Cobb-Douglas	47%	100%	72%	70%
Convex Hull	37%	28%	100%	43%
Leontief	37%	30%	57%	100%

and for two of these models, as bad as our forecast is, it is nevertheless the best in the basket of models. There are a few industries where our framework performs significantly better than the competing models.[42] In summary, the predictive power of our framework consistently provides a labour share forecast that is at least as good as all other models pooled together.

We must acknowledged that not taking into account technical change through a Leontief function or considering a fixed share with a Cobb-Douglas function gives satisfactory results in a large majority of industries. To ensure that our rough method of estimating substitution elasticities does not disadvantage the CES functions, we report the results including only the sectors for which Young (2013) estimates a substitution elasticity in figure 3.F.17.[43] The results are very similar and the performance of CES remains erratic.

6.4 Sensitivity analysis: testing set size and starting year of the forecast

We test the sensitivity of our forecast to the length of the training set, and more importantly of the starting point of the forecast (especially for the Cobb-Douglas function, since labour share is supposed constant from the last point in the training sample). We have varied the start of the training period from 2010 — meaning that the training set is now 70% of the dataset — to 2018, where we try and forecast only the next year labour share.

Table 3.9 – Comparing the four models predictive power with different starting year of the testing set

	2010	2011	2012	2013	2014	2015	2016	2017	2018
CES	21%	27%	30%	27%	31%	25%	36%	33%	36%
Cobb-Douglas	17%	14%	12%	11%	22%	21%	12%	17%	22%
Convex Hull	32%	35%	38%	36%	27%	37%	35%	27%	31%
Leontief	30%	25%	20%	26%	20%	17%	17%	22%	11%

Table 3.9 summarises the performance of the four models we consider with various starting year for the testing set. Our framework has good performance across time. Let's notice that CES functions perform better on shorter periods of time (1 to 3 years). Two possible explanations are: i) they do not encapsulate induced technical change except for substitution which is a disadvantage over long period of time, ii) on the contrary, linear TFP growth could lead to overestimate technical change.

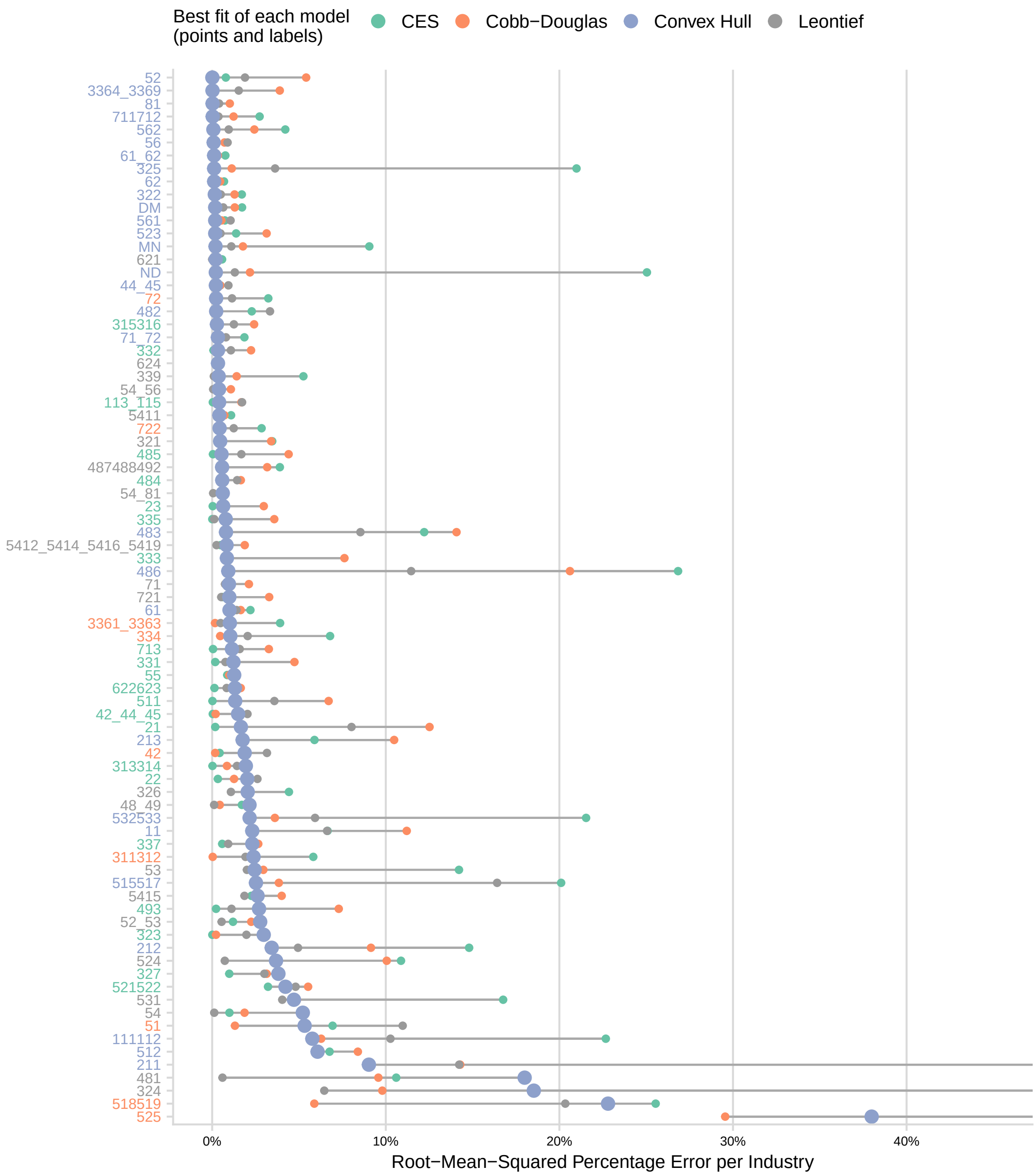
In figure 3.21, we have plotted the forecast of the labour share for 9 forecasting timespan: from 2010-2019 to 2018-2019. The trends confirm the previous assumptions.[44]

[42] 325,ND,483,486.

[43] It does not ensure that it is his elasticity that we use, we retain the best CES specification for this sector.

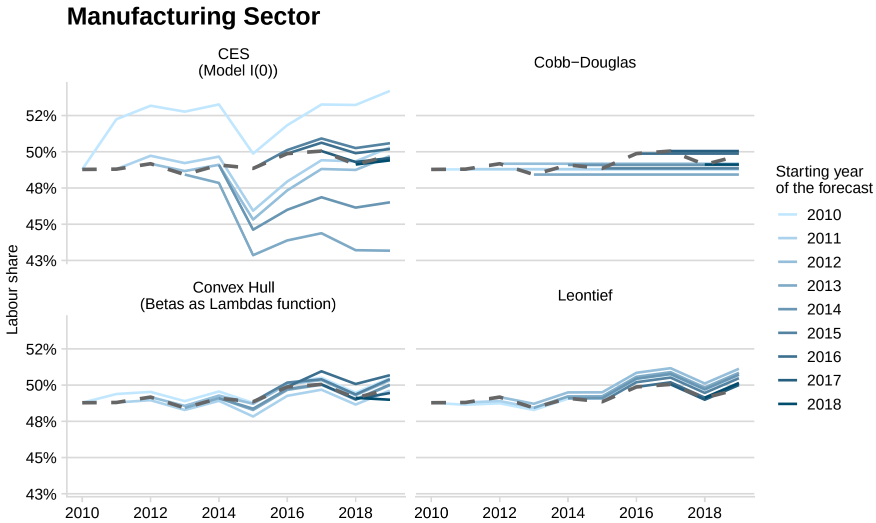
[44] Figures for Agriculture, Finance and Paper industry are available in appendix: Figures 3.F.20,3.F.19,3.F.21.

Figure 3.20 – Forecast of the labour-share per industry and error per category of model



Note: Only the best fit of each model category is retained. The colour of the industry code on the vertical axis indicates the best model for that industry. See appendix, table 3.C.1, for the industries nomenclature.

Figure 3.21 – Forecast of labour share of the manufacturing sector with different length of the training versus testing set



Our framework test gives consistent evolution of labour share over different forecasting periods. The Leontief production function systematically overestimates the labour share: it does not take into account the labour-saving technical change in the manufacturing sector which has had a moderating effect on the labour share in recent years (2016-2019, see figure 3.9). The CES function overestimates technical change with a lower labour share than in reality for the start years 2011-2014, and is rather accurate for the latter.

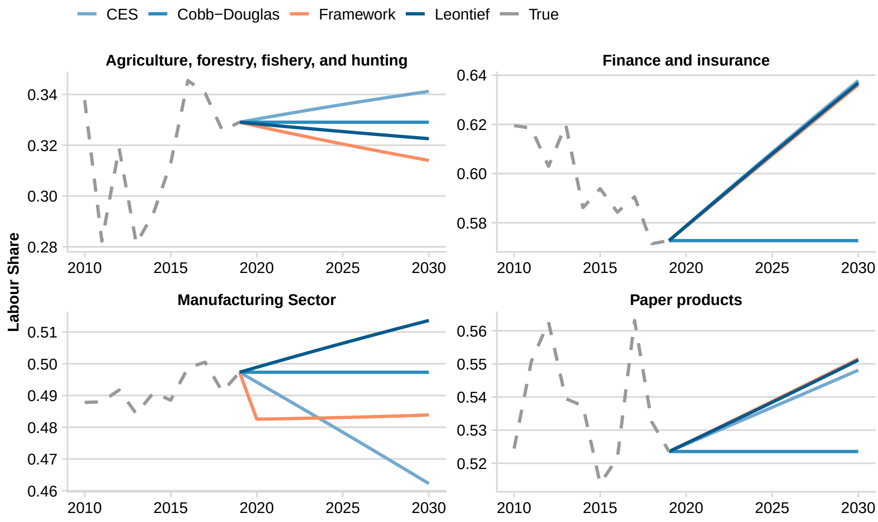
6.5 Policy Impact & Summary

We have shown that our framework ("Convex Hull") allows us to accurately forecast the evolution of the factor shares of almost all 81 sectors of the KLEMS US database. In all cases, our framework is better or as good as the other competing models (CES, Cobb-Douglas and Leontief). Our model is validated by its predictive power. The simplicity of the forecast process of our framework is to be underlined, especially compared to the theoretical difficulties and empirical issues to estimate elasticities of substitution (see for reference Temple (2012); Klump and Saam (2008)).

Note that the effort may seem paltry when a Leontief function can predict the evolution of the labour share with acceptable accuracy. One of the reasons is that technical capital change and labour-saving often compensate each other a to a large extent, leaving technical change with a weak direction in total. The CES functions or our framework provides an understanding and prioritisation of the processes at work.

We can try to make longer term predictions with our model. We assume that the prices of capital and labour follow a linear increase estimated on the 1987-2019 data

Figure 3.22 – Forecast of labour share up to 2030 for four industries



The best specification over the period 2013-2019 of each model is retained.

(see Appendix 3.F, Figure 3.F.23). For the agricultural sector, our model predicts a decline in the labour share to just over 0.31, with a stable net labour-saving technical change (λ_L/λ_K) between 2 and 2.5, (see Figure 3.F.22, Appendix 3.F). The CES function predicts a slow increase in the labour share until 2030. Our framework predicts that the labour share in manufacturing will fall by two percentage points between 2019 and 2020 and then remain stable at 48.5%. The technical change bias remains stable at 1.07. In contrast, we see little difference between the models for the Financial and Paper sectors. Indeed, the difference between these models is the way they encapsulate technical change and reactions to sudden price changes. In the case of a linear price increase most models will have similar reactions. For both sectors, all models predict an increase in the factor share of between 3 and 7 percentage points. For our framework, this is accompanied by an increase in the net-capital bias saving technical change.

7 Energy-saving technical change

(Preliminary results)

The decoupling of the economy from emissions — and in particular, the existence of an absolute decoupling that allows economic growth while reducing emissions — questions the potential of new technologies. Will the deployment of current energy-efficient technologies or future low-carbon innovations be able to reduce our use of fossil fuels? At a pace compatible with climate change?

In this section, we show preliminary results on the extension of our framework to more than two inputs: we add energy in addition to capital and labour, and then material and service as well (KLEMS).

The literature on directed technical change has studied induced environmental and energy innovation for nearly 10 years. Acemoglu et al. (2012) shows that an increase in the price of energy can lead to investment in clean goods rather than in dirty goods, with a significant pathway dependency. Although the study of technologies and the environment is much older (Popp et al., 2010). Recently a growing number of articles and literature reviews have attempted to summarise the advances in the field (Hassler et al., 2021; Hémous and Olsen, 2021; Kruse-Andersen, 2019; Popp, 2019; Hassler et al., 2012), to which we refer and we focus on only a few salient papers for our study.

Market-based instruments have a clear impact and positive impacts on green innovation, although the magnitude varies across studies. It applies to all types of market instruments: Aghion et al. (2016) shows positive relationship between green innovation and fuel taxes in the automotive industries that could lead to redirect investments towards the clean good. Franco and Marin (2017) show that innovation reacts positively to more stringent environmental regulation, and especially that there is an innovation induced by environmental taxation (weak Porter hypothesis). Calel and Dechezlepretre (2016) shows that there is a weak but positive relationship between being part of the European ETS and green innovation.

Dechezleprêtre et al. (2019) shows that market-based instruments have an action on green R&D but are limited to mature technologies; welfare benefits, for instance in terms of knowledge spillover are thus also limited. It calls for public R&D subsidies technologies at more early stage to foster potentially greater future benefits Edenhofer et al. (2021) emphasises the same conclusion of mixing carbon pricing and subsidies. Technology policies outside of ETS and carbon pricing have been very efficient to bring renewable energy to the market, they have contributed greatly to the decrease in emissions, but these policies are not adapted to spread these widely at the envisaged massive scale. The price of carbon is therefore central to the deployment of these technologies.

Verdolini et al. (2021) highlights that the cost of the green technologies (compared to the price of energy) is of course a necessary condition for the adoption of energy savings technology, but other barriers exist, among else: the proliferation of green technologies at early stages in the same niches thus limiting the development of many of them; various environments and diverse agents with different needs and expectations, and economic interest groups lobbying (Chapter 4 of this dissertation dwells on adoption barriers for natural gas trucks for supply chain in France).

The literature on directed technical progress applied to the environment is divided into two types of studies (Hémous and Olsen, 2021): models studying the substitution between two goods dirty and clean (Acemoglu et al., 2012); or models modelling energy as a primary input complementary to labour and capital (Smulders and de Nooij, 2003; Hassler et al., 2021). We contribute to this second strand of literature with the application of our framework to energy, labour and capital.

In this section, we briefly present the theoretical model extended to five inputs. Then, we show that our framework give consistent results when including more inputs. We determine the impacts of price increases on energy-saving technical change and the impacts of energy prices on the other directions of technical changes. Finally, we show that labour and energy-saving technical change are highly correlated.

7.1 Extension of the theoretical model

The framework presented in section 2 can easily be extended to more than two inputs although the geometrical intuition is less easily pictured in higher dimensions. We can assume that in a world with n inputs, technical change can be broken down into n factor-saving directions. Then, we express the global production function that maximises the output by allocating inputs to the different local factor-saving production functions. There is a hyperplan $\mathscr{H}$ in n dimensions where we use the five production functions. It contains the origin O, the point M_1 that we want to reach from M_0, and the characteristic points of the local factor-saving Leontief production functions.
The expressions of λs for 5 inputs — K, L, E, M and S — are

$$\begin{cases} \lambda_K = \dfrac{-Y_0 + K_0 p_{K_1} + L_0 p_{L_1} + E_0 p_{E_1} + M_0 p_{M_1} + S_0 p_{S_1}}{Y_0 - L_0 p_{L_1} - E_0 p_{E_1} - M_0 - p_{M_1} - S_0 p_{S_1}} \\ \lambda_L = \dfrac{-Y_0 + K_0 p_{K_1} + L_0 p_{L_1} + E_0 p_{E_1} + M_0 p_{M_1} + S_0 p_{S_1}}{Y_0 - K_0 p_{K_1} - E_0 p_{E_1} - M_0 - p_{M_1} - S_0 p_{S_1}} \\ \lambda_E = \dfrac{-Y_0 + K_0 p_{K_1} + L_0 p_{L_1} + E_0 p_{E_1} + M_0 p_{M_1} + S_0 p_{S_1}}{Y_0 - K_0 p_{K_1} - L_0 p_{L_1} - M_0 - p_{M_1} - S_0 p_{S_1}} \\ \lambda_M = \dfrac{-Y_0 + K_0 p_{K_1} + L_0 p_{L_1} + E_0 p_{E_1} + M_0 p_{M_1} + S_0 p_{S_1}}{Y_0 - K_0 p_{K_1} - L_0 p_{L_1} - E_0 p_{E_1} - S_0 p_{S_1}} \\ \lambda_S = \dfrac{-Y_0 + K_0 p_{K_1} + L_0 p_{L_1} + E_0 p_{E_1} + M_0 p_{M_1} + S_0 p_{S_1}}{Y_0 - K_0 p_{K_1} - L_0 p_{L_1} - E_0 p_{E_1} - M_0 - p_{M_1}} \end{cases} \tag{3.37}$$

To find β_K for instance, we solve the following equation:

$$\begin{vmatrix} 1 & 0 & 0 & 0 & 0 & \dfrac{K_0}{1+\lambda_K} \\ 0 & 1 & 0 & 0 & 0 & L_0 \\ 0 & 0 & 1 & 0 & 0 & E_0 \\ 0 & 0 & 0 & 1 & 0 & M_0 \\ 0 & 0 & 0 & 0 & 1 & S_0 \\ p_{K_1} & p_{L_1} & p_{E_1} & p_{M_1} & p_{S_1} & Y_0 \end{vmatrix} = 0. \tag{3.38}$$

The pattern appears clearly to solve and find β_L, β_E, β_M, β_S

7.2 Data & Method

We estimate the λs and βs on the U.S. (1986-2019) and EU+ KLEMS v2008 (1970-2005) databases because they are the only databases with the five readily available inputs.

We compute the λs and βs for several framework, in addition to the framework (K, L) already studied in the previous sections, we investigate the (K, E), (L, E) and (K, L, E, M, S) frameworks.

7.3 Technical change trends across frameworks

In this section, we investigate whether the value of technical change intensities (λs) depends on the inputs included in the framework. It has a very practical application: to estimate the effects of energy prices on energy-saving technical change, we may either use the full framework (K, L, E, M, S), or two-inputs framework, (K, E) and (L, E), or three-inputs frameworks: (K, L, E).

First, we find that λ_E is larger than any other direction, with a ratio of about 10:1. It is consistent across frameworks.[45] It is unlikely to be linked to the reporting unit for energy consumption since quantities and prices are reported as indexes relative to 2010 values in the KLEMS databases. Moreover, relative variations of energy price over the period are similar to whose of all inputs. Very few industries have a ratio λ_L/λ_E or λ_K/λ_E that exceeds 1. We are therefore always more energy-saving than capital or labour-saving.

For each industry, the ratios of λs, i.e. the net direction of technical change (such as λ_L/λ_K), are almost similar across the frameworks (Figure 3.23). In particular, the value of λ_L/λ_K is almost similar on all frameworks. However, the values of the λs in the different frameworks can vary significantly, and even change sign.

This means that the ratio of λs and the trends in the net factor-saving technical change can be interpreted within any framework.

However, the estimate of the relationship between price increases and the intensity of technical change and prices might depend on the framework used. To conclude to a robust effect, we might need either the result to be validated using several frameworks or to regress the ratio of λs en prices. Note that the variety of methods giving consistent results on Hicks's hypothesis in section 5 is robust relative to these findings.

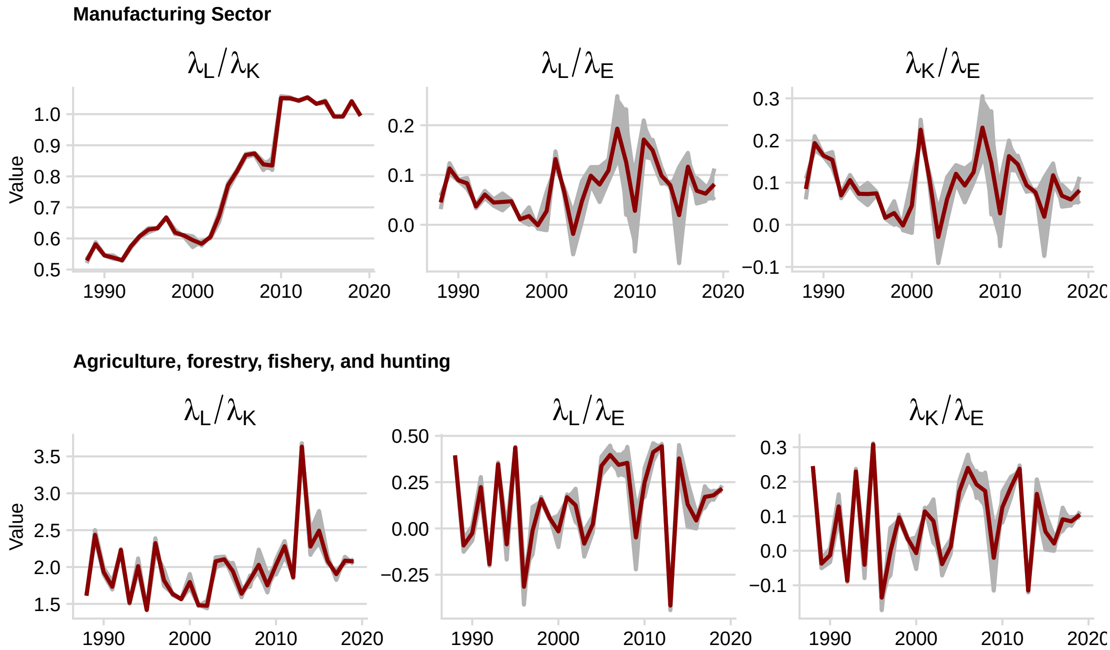
7.4 Is the green technical change price-induced?

As in section 5, we study whether technical change is price-induced. We regress the intensity of technical change in a factor-saving direction on price variations. Sectoral prices are instrumented by national prices, first-differenced to get stationary time-series. We compare the estimates to estimates on randomly generated data.

For two-inputs framework: (K, E) or (L, E) we can re-use the same randomly generated data as in section 5. To compare the estimates in frameworks (K, L, E) and (K, L, E, M, S), we run simulations by creating randomly generated sectors with 3 or 5 inputs.

[45] In absolute value, λ_E is greater than λ_L or λ_K for 95.3% to 97.4% of observations. In the framework KLEMS, λ_E is greater than λ_K in 95.3% of observations and In the framework LE, λ_E is greater than λ_L in 97.34% of observations.

Figure 3.23 – Factor-saving technical change across multiple frameworks — Manufacturing & Agricultural sectors U.S.



Average of the λs values over the four out of five frameworks including this input (E is present in KE, LE, KLE and KLEMS). The red line is the average value, the grey area shows all the values found in the 4 frameworks. Data: KLEMS US 1986-2019

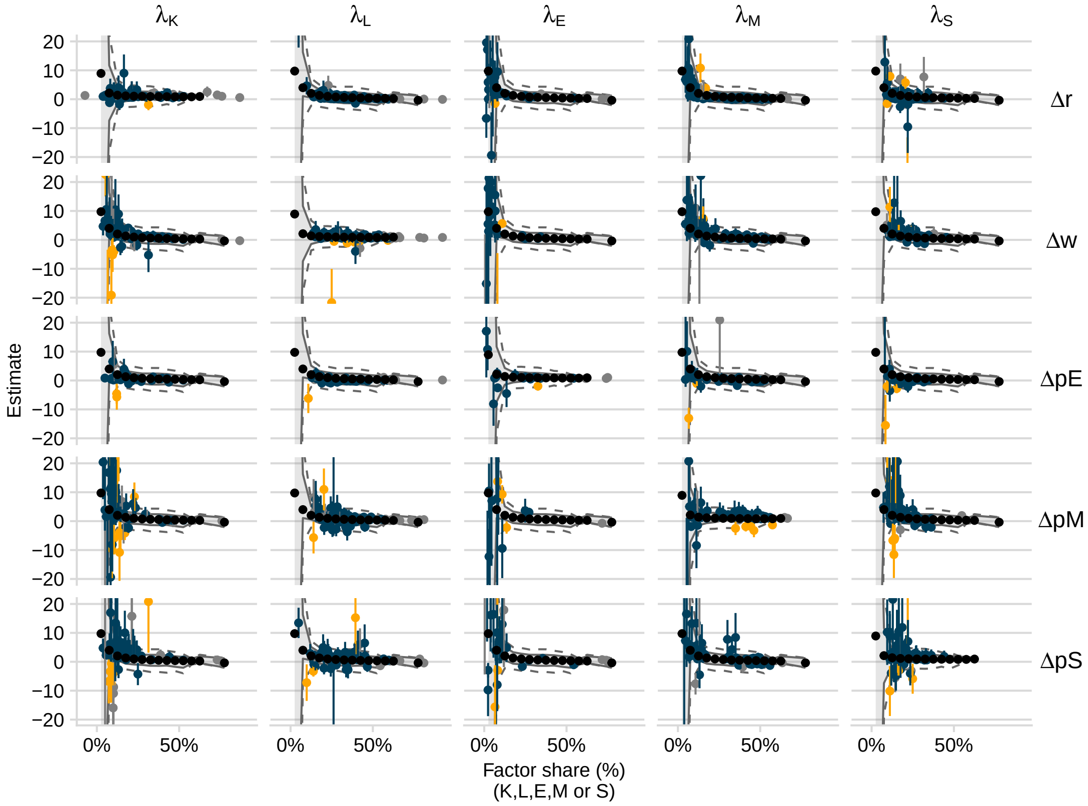
Directed technical change in a KLEMS framework

In this section, we test Hicks's hypothesis on the intensities of technical change derived in the previous section, by inferring a relationship with the variations in the prices of the inputs. We estimate the intensity of technical change separately:

$$\begin{aligned}
\lambda_K &= a_w^K \Delta w + a_r^K \Delta r + a_{p_E}^K \Delta p_E + a_{p_M}^K \Delta p_M + a_{p_S}^K \Delta p_S + \varepsilon \\
\lambda_L &= a_w^L \Delta w + a_r^L \Delta r + a_{p_E}^L \Delta p_E + a_{p_M}^L \Delta p_M + a_{p_S}^L \Delta p_S + \varepsilon \\
\lambda_E &= a_w^E \Delta w + a_r^E \Delta r + a_{p_E}^E \Delta p_E + a_{p_M}^E \Delta p_M + a_{p_S}^E \Delta p_S + \varepsilon \\
\lambda_M &= a_w^M \Delta w + a_r^M \Delta r + a_{p_E}^M \Delta p_E + a_{p_M}^M \Delta p_M + a_{p_S}^M \Delta p_S + \varepsilon \\
\lambda_S &= a_w^S \Delta w + a_r^S \Delta r + a_{p_E}^S \Delta p_E + a_{p_M}^S \Delta p_M + a_{p_S}^S \Delta p_S + \varepsilon,
\end{aligned} \tag{3.39}$$

First, we notice that the increase of all prices except capital triggers a technical change capital-using (Figure 3.24). An increase in the price of service leads to service-saving technical change for a number of industries (bottom-right panel), which

Figure 3.24 – Estimation of the relationship between the intensity of technical change ($\lambda_{(K,L,E,M,S)}$) and price variation ($\Delta r, \Delta w, \Delta p_E, \Delta p_M, \Delta p_S$)



Note: The point estimates are plotted against the factor share of the input corresponding to the regressed λ — real or randomly generated. The first column is plotted against capital share, and the second, labour share. For more details, see note in figure 3.16 in section 5.7. Data: KLEMS US (1986-2019), KLEMS EU+ v2008 (1970-2005) contradicts Hicks's hypothesis. Price increase seems to have little to no effects significantly different from randomly generated data on λ_E et λ_L.

Overall, using the (K, L, E, M, S) framework gives poor results. A key reason is that the estimates are dependent on the five factor share and the figure 3.24 can only show one (x-axis, estimates of λ_X are plotted against α_X, cf. the note of Fig. 3.24). As the share of energy is relatively small compared to other inputs, the estimates of λ_E are close to zero on the x-axis, where the dispersion of estimates on randomly generated data is maximum.

Energy saving technical change on parsimonious frameworks

In this section, we use the (K, E) and (L, E) frameworks to estimate the effect of energy prices on technical change.

Framework (K, E) We find a relationship significantly more positive than estimates on randomly generated data between capital price and energy-saving technical change (with two exceptions,[46] where effect is negative). Conversely, the estimates of capital-saving technical change following an increase in the price of energy are significantly different from random data but very close to zero. The few significant estimates of the relationship between energy-saving technical change and energy prices give mixed evidence.

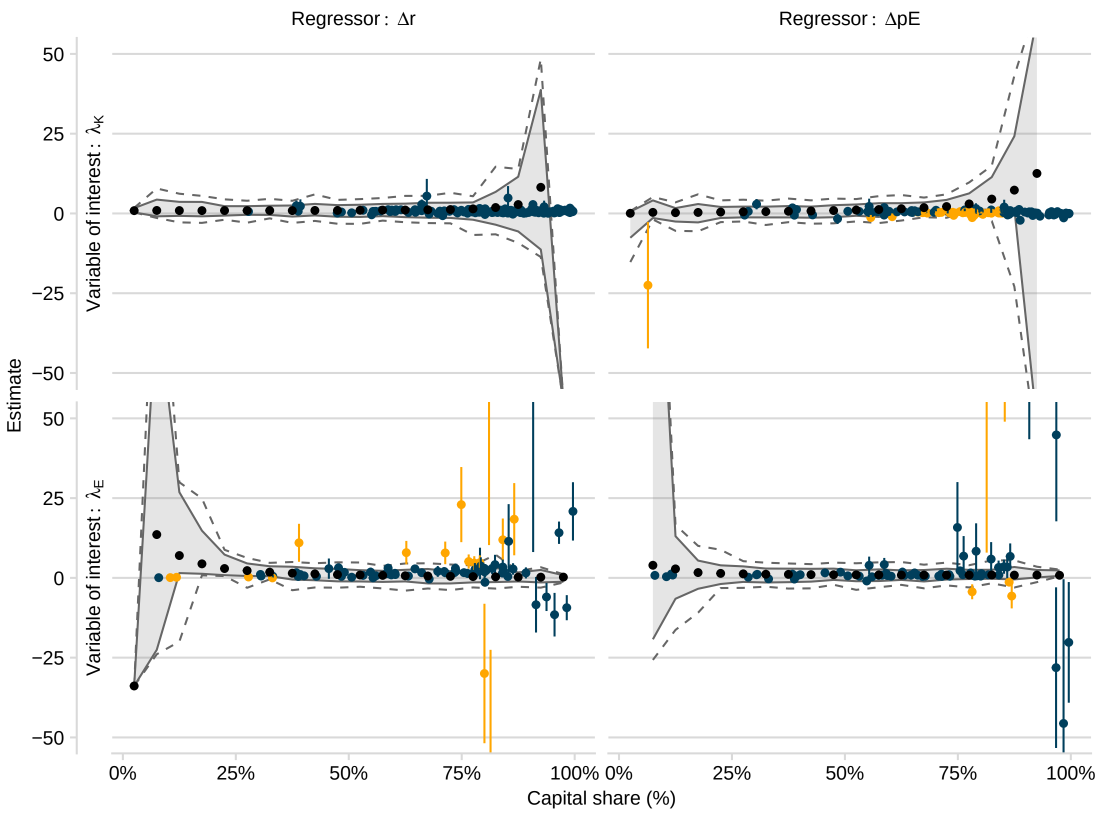
Framework (L, E) Increases in energy prices are not significantly correlated with λ_L. Conversely, increases in wages are correlated with energy-using technical change: the estimates are small but more significantly negative than the estimates on randomly generated data (Figure 3.G.24, appendix 3.G).

The estimates of the relationship between labour and energy net technical change (λ_L/λ_E) is more significant (Figure 3.G.24). An increase in the cost of labour is significantly positively correlated with λ_L/λ_E. In one sector (utilities, Austria), we find an increase in λ_E relative to λ_L. Both effects are in line with Hicks's hypothesis.

Summary We find no energy-saving technical change induced by energy prices. However, we find that energy-saving technical change depends on the cost of labour and capital. We find that increases in the cost of capital are correlated with energy-saving technical change while increases in the cost of labour are correlated with energy-using technical change. Interpretation is tricky, but automation could link capital, labour and energy as follows: increases in wages would mean more automation with energy-intensive machinery. Conversely, increases in the cost of capital increases might put a stop to automation, and thus to energy intensity.

[46] These sectors are paper and printing, sales of motor vehicles, wholesale and retail in Portugal, four public administration in various countries, textile and electrical equipment industries.

Figure 3.25 – Estimation of the relationship between the intensity of technical change ($\lambda_{(K,E)}$) and price variation ($\Delta r, \Delta p_E$)



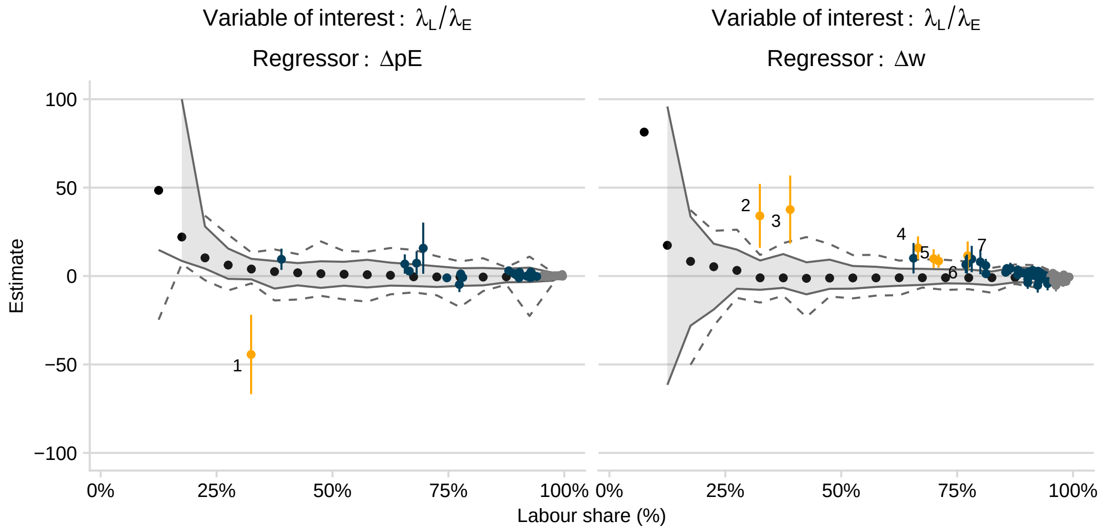
Note: The point estimates are plotted against the capital share. See figure 3.24. Data: KLEMS US (1986-2019), KLEMS EU+ v2008 (1970-2005)

7.5 Energy and Labour biases of green technical change

In this section, we assess whether a factor-saving technical change is correlated with technical change on another direction. We check the correlation of factor-saving technical change intensities in a 5-input framework (K, L, E, M, S) on the KLEMS EU+ v2008 database (Data 1970-2005)

We use a Spearman test to assess the correlation of the series of λ_K, λ_L, λ_E, λ_M and λ_S (Corder and Foreman, 2014). A Spearman test allows us to test for a non-linear relationships between the λs. It compares the rank of the observations in the series and not their value, which makes it less sensitive to outliers. There are indeed several λs "surges" in our results, and a Pearson test would be confounded by outliers. We have

Figure 3.26 – Estimation of the relationship between the intensity of technical change (λ_L/λ_E) and price variation ($\Delta W, \Delta p_E$)



Note: The point estimates are plotted against the labour share. See figure 3.24. Data: KLEMS EU+ v2008 (1970-2005)

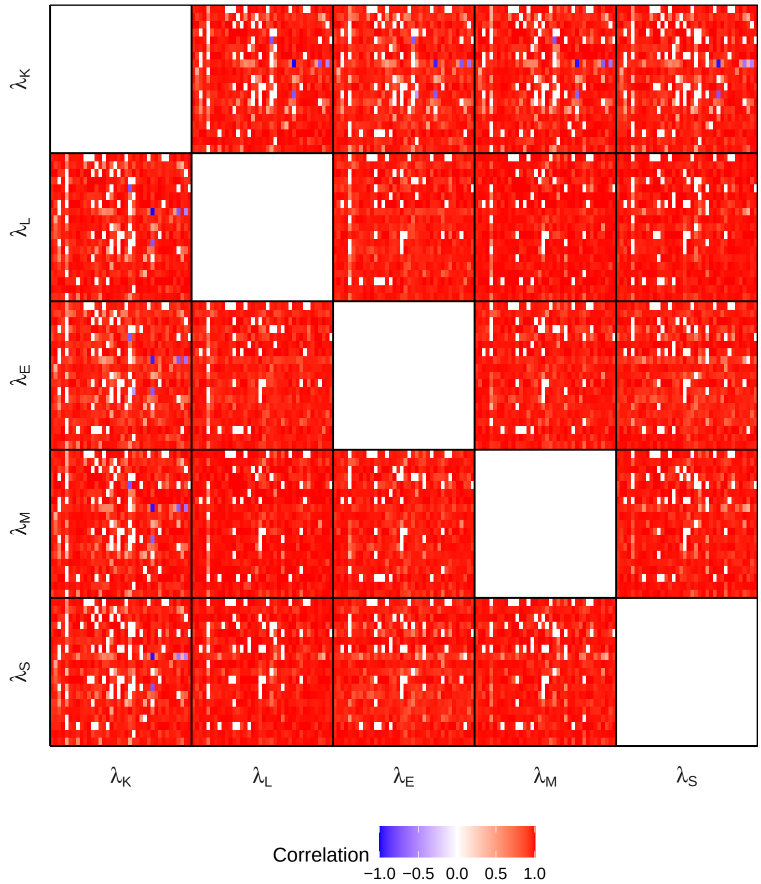
restricted the sample to observations for which $\lambda_E > -1$, i.e. where the quantity of energy used is positive.[47]

Correlation We find that the intensity of energy-saving technical change is largely correlated with the other dimensions of technical change (Figure 3.27). Only the intensity of capital-saving technical change shows non-significant or negative relationships with the other intensities of technical change. This shows, i) that the results are not biased by the framework, ii) that capital-saving technical change can be both labour-saving or labour-using and energy-saving or energy-using.

We conclude that energy-saving technical change is likely to be labour-saving as well. The expected effects on households are ambiguous: if energy-saving innovations are labour-saving, it means that the overall technical change is likely to have a capital bias which would advantage the richer households with capital income.

[47] If we plot the heatmap on all observations, then λ_E is weakly correlated with all the other λs. In the case of the previous regressions, it reflects a strong reaction to prices or other events, but it biases the correlation between λs.

Figure 3.27 – Heatmap of correlation between the intensities of technical change in a 5-inputs (K, L, E, M, S) framework



Data: KLEMS EU+ v2008 (1970-2005)

8 Conclusion

In this chapter, we have exposed a framework disentangling the directions of technical change and factor substitution. We show that starting with a Leontief production function, we can describe any technical change that reaches a state of production — output and input — that is not on the function. We shift the Leontief function in a purely labour-saving direction and in another purely capital-saving direction, thus creating two local Leontief production functions. The global production function that can explain the new state of production is the convex hull of these two factor-saving functions.

This framework allow us to compute labour and capital-saving technical change indicators for any industry and country between two consecutive years. It is a simple and flexible framework that can easily be extended to n inputs.

We have performed a number of analyses with the framework described. We compute the technical change indicators on the KLEMS database for the U.S., European countries and some other OECD countries.

First, we conclude that most countries and industries in the U.S. and Europe are net capital-saving — or labour-biased — with a growing trend towards labour-saving technical change. We can relate the trends in the direction of technical change to new technologies or specific national events. This makes our framework a prime tool for studying and comparing the dynamics of technical change in different countries and industries.

Second, and this is the main result of the chapter, we prove that Hicks's hypothesis of price-induced innovation holds for a large number of industries. That is, industries use factor-saving innovation to save on a factor becoming relatively more expensive. Although we have some mixed evidence —either non significant or contradicting Hicks's hypothesis — the results in line with Hicks's hypothesis seem robust enough to conclude that there is price-induced technical change.

Third, our framework is able to accurately forecast the dynamics of labour and capital shares in value-added. We can conclude that its descriptive and forecasting power are at least equal to other production function such as CES functions, Cobb-Douglas or Leontief production functions. It validates our framework and opens new research avenues on the evolution of technical change in the short term using this framework.

Fourth, a preliminary analysis extends the framework to five inputs: capital, labour, energy, material and service. Our framework is consistent: the trends in technical change are the same no matter how many more inputs are included in the framework (either the absolute intensity of a specific factor-saving technical change or the ratio of two directions of technical change — the bias of technical change — are the same in a (K, L) or (L, E) and a (K, L, E, M, S) framework. The preliminary results point to no evidence of energy-saving technical change induced by the price of energy. However, increases in the prices of labour or capital seems to induce energy-saving technical change.

Despite the strong hypothesis of using Leontief production functions, the growth and technical change accounting framework developed in this chapter have proven to be a useful addition to both the theoretical and the empirical literature. Future work includes examining other determinants of technical change beyond price, such as R&D expenses, patenting, or tax policy; extending the analysis to multi-input production functions and integrating this modelling of technical change into general equilibrium models.

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Appendix

Nous voulons, tant ce feu nous brûle le cerveau,
Plonger au fond du gouffre, Enfer ou Ciel, qu'importe ?
Au fond de l'Inconnu pour trouver du nouveau !

Charles Baudelaire, "Le Voyage", *Les Fleurs du Mal*

3.A Proof of Lemmas

Proof of Lemma 1

Proof. F and F' are two Leontief production functions:

$$\begin{array}{rlcl} F: & \mathbb{R}_+ \times \mathbb{R}_+ & \to & \mathbb{R}_+ \\ & (K, L) & \mapsto & F(K, L) = Y = Y_0 \cdot \min\left(\dfrac{K}{K_0}, \dfrac{L}{L_0}\right) \end{array}$$

with $Y_0 = F(K_0, L_0)$.

We can write the intensive production function associated with F:

$$\begin{array}{rlcl} f: & \mathbb{R}_+ & \to & \mathbb{R}_+ \\ & k & \mapsto & f(k) = y = y_0 \cdot \min\left(\dfrac{k}{k_0}, 1\right) \end{array}$$

with $k = K/L$, $y = Y/L$, $k_0 = K_0/L_0$ and $y_0 = Y_0/L_0$. k_0 is called the characteristic ratio of the function F.

$$\begin{array}{rlcl} F': & \mathbb{R}_+ \times \mathbb{R}_+ & \to & \mathbb{R}_+ \\ & (K, L) & \mapsto & F'(K, L) = Y = Y'_0 \cdot \min\left(\dfrac{K}{K'_0}, \dfrac{L}{L'_0}\right) \end{array}$$

that we can write intensively

$$\begin{array}{rlcl} f': & \mathbb{R}_+ & \to & \mathbb{R}_+ \\ & k & \mapsto & f'(k) = y = y'_0 \cdot \min\left(\dfrac{k}{k'_0}, 1\right) \end{array}$$

with $k'_0 = K'_0/L'_0$ and $y'_0 = Y'_0/L'_0$.

A line in $\mathbb{R}^2$ is a set $\{(x,y) \in \mathbb{R}^2_+ | ax + by + c = 0, (a,b) \neq 0, (a,c,b) \in \mathbb{R}^3\}$. In the case of a the line going through the origin then $c = 0$, hence the line is then defined as $ax + by = 0$.

The following sub-lemma allows us to reason in intensive form rather than with the full extensive functions for the sake of simplicity.

Sub-Lemma The intersection of the Leontief functions exists and corresponds to a line in $\mathbb{R}^2$ if and only if there is an intersection of the intensive functions in $\mathbb{R}$ that forms a point:

- If F and F' intersect as a unique line, then we can define a unique alpha defining this line and the intersection point for the two intensive functions:
  $\exists!\ \alpha > 0 \,|(\forall (K,L) > 0, K/L = \alpha \implies F(K,L) = F'(K,L))$.
  Therefore, $\forall (K,L) > 0,$ such as $K/L = \alpha,$ then $L \cdot F(K/L,1) = L \cdot F'(K/L,1) \Rightarrow \exists!\ \alpha > 0 | f(\alpha) = f'(\alpha)$
- If $\exists!\, k^*, f(k^*) = f'(k^*)$ then $\forall (K,L) > 0 | K/L = k^* \Rightarrow K - k^* L = 0$, which is the equation of a line going through the origin. Uniqueness of the point triggers the uniqueness of the intersecting line.

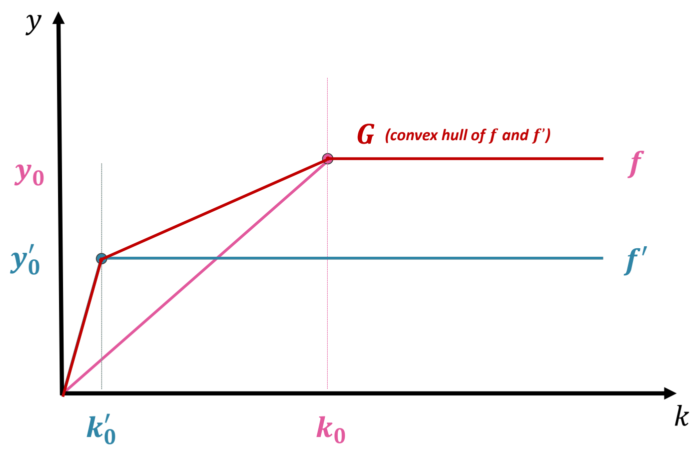
Intuitively, in intensive use, the intersection can only take place once the first function is saturated, i.e. at $k > k'_0$, and the second not yet, $k < k_0$.
We now prove that the intersection exists in the intensive framework and is unique.

Existence If there is no intersection of f and f', then as they are continuous functions, then $\forall k > 0, f(k) > f'(k)$ (without losing generality). Therefore, $\forall L > 0, K > 0, L \cdot F(K/L,1) > L \cdot F'(K/L,1)$, leading to $\forall L > 0, K > 0, F(K,L) > F'(K,L)$ contradicting the non-dominance of the two functions.

Uniqueness Let us have $k'_0 = K'_0/L'_0 < k_0 = K_0/L_0$ without losing generality. k_0 and k'_0 cannot be equal without f. Hence, $\exists \alpha > 1 | \alpha k'_0 = k_0$

1. If there is an intersection point on $[k_0, +\infty[$, then $\exists k^* > k_0 | f(k^*) = f'(k^*) = y^*$. Yet, $\forall k \geq k_0, f(k) = f(k_0) = y_0$ and $f'(k) = f'(k'_0) = y'_0$, hence, $y_0 = y'_0 = y^*$.
   We conclude that $\forall k > 0, f(k) = y_0 \min(\frac{k}{k_0}, 1) = y_0 \min\left(\frac{k}{k'_0 \alpha}, 1\right) \leq y_0 \min\left(\frac{k}{k'_0}\right) = f'(k)$, which means f' dominates f contradicting the hypothesis.
2. If there is an intersection point at (k^*, y^*) such that $k^* \in]0, k'_0[$ and $f(k^*) = f'(k) = y^*$.
   Since $k/k_0 < k/k'_0 < 1$, then $f(k^*) = y_0 \cdot \min\left(\frac{k^*}{k_0}, 1\right) = \frac{y_0 k^*}{k_0} = \frac{y'_0 k^*}{k'_0}$. Since $k^* > 0$, hence $\frac{y_0}{k_0} = \frac{y'_0}{k'_0}$. $\forall k > 0, f(k) = y_0 \cdot \min(k/k_0, 1) = \frac{y_0}{k_0} \cdot \min(k, k_0) =$

Figure 3.A.1 – Illustration intensive framework Lemma 2



$\frac{y_0'}{k_0'} \cdot \min(k, k_0) \geq \frac{y_0'}{k_0'} \cdot \min(k, k_0') = f'(k)$ which means f' dominates f contradicting the hypothesis.

3. If there is an intersection point (k^*, y^*) such that $k^* \in]k_0', k_0[$ and $f(k^*) = f'(k) = y^*$. The equation $f(k^*) = f'(k^*) \Leftrightarrow \frac{y_0 k^*}{k_0} = y_0'$ has a unique solution on $]k_0', k_0[$.

The intersection of two production functions which do not dominate one another exists and is unique. □

Proof of Lemma 2

Proof. **1. Maximum production function**

Let us have two non-dominated Leontief functions, F and F', defined by their characteristic ratio, respectively $k_0 = \frac{K_0}{L_0}$ and $k_0' = \frac{K_0'}{L_0'}$, and $y_0 = \frac{F(K_0,L_0)}{L_0}$ and $y_0' = \frac{F(K_0',L_0')}{L_0'}$. Without losing generality, let suppose that $y_0 > y_0'$ and $\frac{K_0'}{L_0'} < \frac{K_0}{L_0}$. It stems that $\frac{y_0'}{k_0'} > \frac{y_0}{k_0}$ The set-up is summarised in figure 3.A.1. The two functions intersect and their intersection is a line, which means that the two intensive functions intersect in a single point (Lemma 1).

Let first prove that at capital-labour ratios not located between the two functions' characteristic ratios, it is optimal to use only one of the two local production functions, then that between their characteristic ratios it is optimal to allocate some inputs to both production functions.

If $\bar{k} < k'_0 \quad \forall \bar{K}, \bar{L} > 0,\ \alpha, \beta > 0,$

$$\begin{aligned}
&F'(\bar{K},\bar{L}) - F'(\alpha\bar{K},\beta\bar{L}) - F((1-\alpha)\bar{K},(1-\beta)\bar{L}) \\
&= y'_0\bar{L}\min\left(\frac{\bar{k}}{k'_0},1\right) - y'_0\bar{L}\min\left(\frac{\alpha\bar{k}}{k'_0},\beta\right) - y_0\bar{L}\min\left(\frac{(1-\alpha\bar{k})}{k_0},1-\beta\right) \\
&= y'_0\bar{L}\frac{\bar{k}}{k'_0} - y'_0\bar{L}\min\left(\frac{\alpha\bar{k}}{k'_0},\beta\right) - y_0\bar{L}\min\left(\frac{(1-\alpha\bar{k})}{k_0},1-\beta\right) \\
&\geq y'_0\bar{L}\frac{\bar{k}}{k'_0} - y'_0\bar{L}\frac{\alpha\bar{k}}{k'_0} - y_0\bar{L}\frac{(1-\alpha\bar{k})}{k_0} \\
&= \bar{L}(1-\alpha)\left(\frac{y'_0}{k'_0} - \frac{y_0}{k_0}\right) \\
&\geq 0\,.
\end{aligned} \tag{3.40}$$

It comes easily that if $\bar{k} < k'_0$, $F'(\bar{K},\bar{L}) > F(\bar{K},\bar{L})$, since $y'_0/k'_0 > y_0/k_0$. On $[0,k'_0]$, using the function F' is always more efficient in terms of output than using F or a combination of F and F'.

If $\bar{k} > k_0$ Likewise, $\forall \bar{K}, \bar{L} > 0,\ \alpha, \beta > 0$, if $\bar{k} > k_0$, $F'(\bar{K},\bar{L}) < F(\bar{K},\bar{L})$, since $y_0 > y'_0$

$$\begin{aligned}
&F(\bar{K},\bar{L}) - F'(\alpha\bar{K},\beta\bar{L}) - F((1-\alpha)\bar{K},(1-\beta)\bar{L}) \\
&= y_0\bar{L} - y'_0\bar{L}\min\left(\frac{\alpha\bar{k}}{k'_0},\beta\right) - y_0\bar{L}\min\left(\frac{(1-\alpha\bar{k})}{k_0},1-\beta\right) \\
&\geq y_0\bar{L} - y'_0\bar{L}\beta - y_0\bar{L}(1-\beta) \\
&= \bar{L}\beta\left(y_0 - y'_0\right) \\
&\geq 0\,.
\end{aligned} \tag{3.41}$$

On $[k_0, +\infty]$, using the function F is always more productive than using F' or a combination of F and F'

If $k'_0 < \bar{k} < k_0$ Let's assume that for $\bar{k} \in [k'_0, k_0]$, we use a combination of the two functions F and F' such that $K, K', L, L' > 0$.

We set:

$$\begin{aligned}
G(K,K',L,L') &= Y_0\min\left(\frac{K}{K_0},\frac{L}{L_0}\right) + Y'_0\min\left(\frac{K'}{K'_0},\frac{L'}{L'_0}\right) \\
&= y_0 L\min\left(\frac{k}{k_0},1\right) + y'_0 L'\min\left(\frac{k'}{k'_0},1\right) \\
&\leq y_0 L + y'_0 L'\,.
\end{aligned} \tag{3.42}$$

The maximum of G is then $\forall K, K', L, L',\ G^* = y_0 L + y'_0 L'$. For any given $(\bar{K},\bar{L})$, the maximum G^* is reached for all K, K', L, L' if $K/L = k_0$ and $K'/L' = k'_0$.

Since $\bar{K} = K + K'$ and $\bar{L} = L + L'$, it follows that

$$\begin{cases} L = & \bar{L}\dfrac{\bar{k} - k_0'}{k_0 - k_0'} \\ L' = & \bar{L}\dfrac{k_0 - \bar{k}}{k_0 - k_0'} \\ K = & k_0 L = \bar{L}\dfrac{k_0(\bar{k} - k_0')}{k_0 - k_0'} \\ K' = & k_0' L' = \bar{L}\dfrac{k_0(k_0 - \bar{k})}{k_0 - k_0'} \end{cases} . \tag{3.43}$$

which check that $K/L = k_0$ and $K'/L' = k_0'$.

Hence, from (3.43):

$$G^*(\bar{K}, \bar{L}) = \bar{L}\left(y_0' \frac{k_0 - \bar{k}}{k_0 - k_0'} + y_0 \frac{\bar{k} - k_0'}{k_0 - k_0'} \right) . \tag{3.44}$$

We can then show that if $k_0' < \bar{k} < k_0$, it is more efficient to use the combination of the two functions (following the previous allocation) than a single function. At given $(\bar{K}, \bar{L})$, $\forall \bar{K}, \bar{L} > 0$,

$$\begin{aligned} & F(\bar{K}, \bar{L}) - F'(K', L') - F(K, L) \\ & = y_0 \bar{L} \min\left(\frac{\bar{k}}{k_0}, 1\right) - y_0' \bar{L} \frac{k_0 - \bar{k}}{k_0 - k_0'} \min\left(\frac{k'}{k_0'}, 1\right) - y_0 \bar{L} \frac{\bar{k} - k_0'}{k_0 - k_0'} \min\left(\frac{k}{k_0}, 1\right) \\ & = y_0 \bar{L} \frac{\bar{k}}{k_0} - y_0' \bar{L} \frac{k_0 - \bar{k}}{k_0 - k_0'} - y_0 \bar{L} \frac{\bar{k} - k_0'}{k_0 - k_0'} \\ & = \bar{L} \frac{k_0 - \bar{k}}{k_0 - k_0'} \left(\frac{y_0}{k_0} k_0' - y_0' \right) \\ & < 0 \, . \end{aligned} \tag{3.45}$$

Likewise,

$$\begin{aligned} & F'(\bar{K}, \bar{L}) - F'(K', L') - F(K, L) \\ & = y_0' \bar{L} - y_0' \bar{L} \frac{k_0 - \bar{k}}{k_0 - k_0'} - y_0 \bar{L} \frac{\bar{k} - k_0'}{k_0 - k_0'} \\ & = \bar{L} \frac{\bar{k} - k_0'}{k_0 - k_0'} \left(y_0' - y_0 \right) \\ & < 0 \, . \end{aligned} \tag{3.46}$$

It proves that for $\bar{k} \in [k_0', k_0]$, our assumption of a non-zero combination of the two functions F and F' was right. We also get that the allocation given in equation (3.43) reaches the maximum output $y_0L+y'_0L'$, thus no other combination can provide a higher output given the constraint on inputs.

The global production function G is the convex hull of the two local production functions, that is the minimal convex set containing all output produced by allocating inputs to the local production functions. G is the maximum output reached by a convex combination of inputs — a linear combination of inputs whose coefficients are positive and sum to one.

2. Market equilibrium

A market equilibrium assumes the existence of a uniquely determined price vector balancing supply and demand. That is typically not possible with Leontief functions, since such a function is not differentiable at its efficient use (at its characteristic ratio k_0).

We show here that the existence of two local Leontief production functions makes the equilibrium price vector uniquely determined.

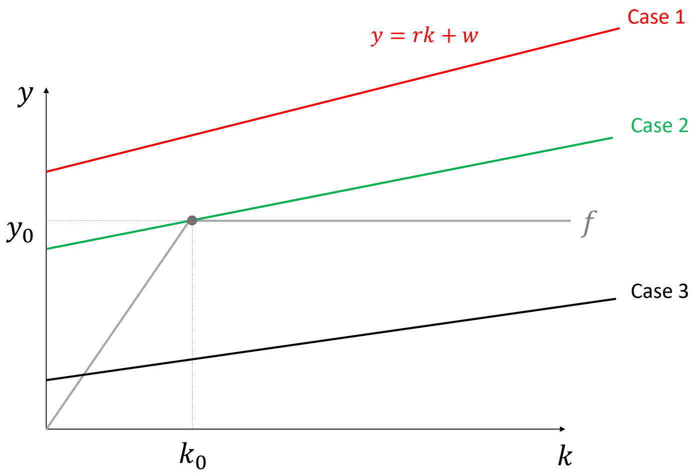
Under an intensive one-Leontief setting, supply of output per capita is given by the curve S: $y_0 \min(\frac{k}{k_0}, 1)$. Let us assume the existence of a wage rate $w > 0$ and a capital rental rate $r > 0$ with the output price normalised to one. The extensive-form profit function is $\Pi(K, L) = F(K, L) - rK - wL$ and the intensive-form profit function is $\pi(k) = \Pi(K/L, 1) = f(k) - rk - w$ (remark that the extensive-form profit function is homogenous of degree 1). There are three situations, as illustrated in Figure 3.A.2:

1. there is no intersection between the two curves. This means that $rk_0 + w > y_0$;
2. there is a single point of intersection (and it has to be at k_0. This means that $rk_0 + w = y_0$;
3. there are two points of intersection. This means that $rk_0 + w < y_0$.

There cannot be more than two intersections points, because if there were then the demand curve would be flat, meaning a zero capital cost. It is neither possible to have the single intersection point at the origin, since it would correspond to a zero wage rate.

1. In this case, profit is negative for all k. Demand for input is null, the market is unbalanced since $y_0 > 0$, hence supply is positive.
2. At the point of use (see Lemma 2, we use each function at its characteristic ratio to maximise output) of the production function, profit is null, and supply and demand balanced out.
3. At k_0, profit is strictly positive, leading to infinite demand for K and L to generate infinite profits. The market is unbalanced.

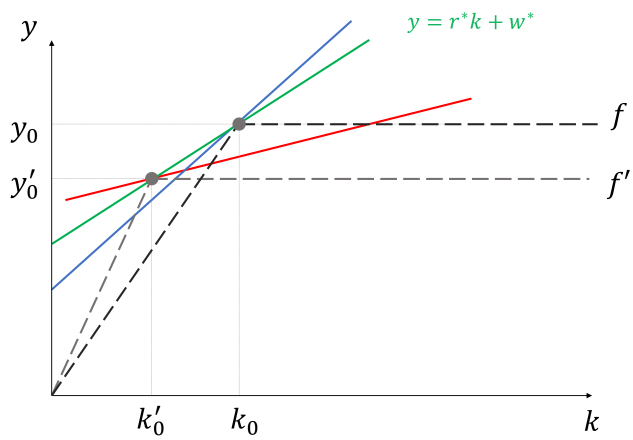
Figure 3.A.2 – One-Leontief intensive setting



Only in case 2 is the market balanced, therefore, in the one-Leontief setting, all (w, r) such that $rk_0 + w = y_0$ are equilibrium price vectors. There is an indeterminacy of the market equilibrium conditions.

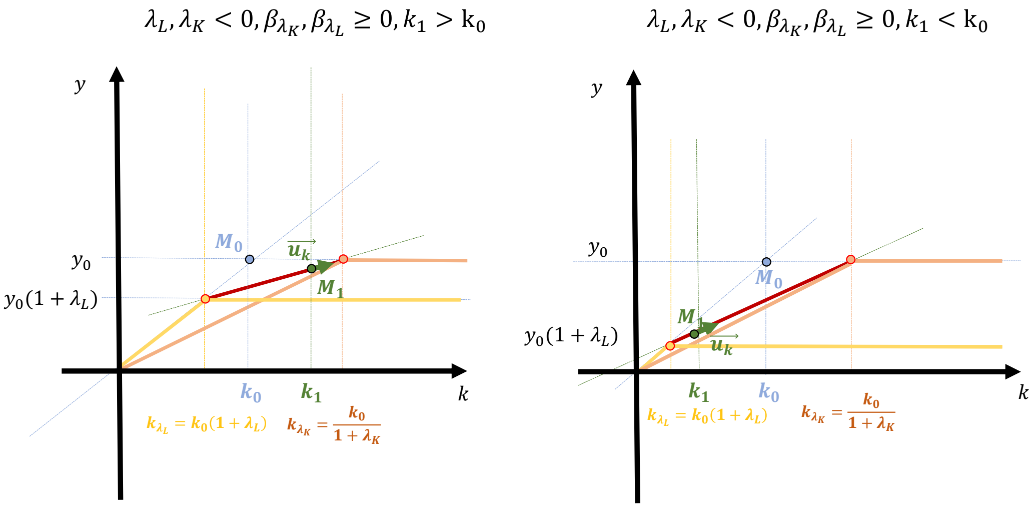
Nevertheless in our situation, we consider a two-Leontief setting, with f and f' as represented in Figure 3.A.3. For this technology menu to exist, the two functions must co-exist within a consistent market. There is a then a single line verifying the nullity of profit at the two characteristic ratios of the two functions. The equilibrium price vector (k^*, w^*) is then defined unambiguously.

Figure 3.A.3 – Two-Leontief intensive setting



□

Figure 3.B.4 – Illustration of a case capital and labour-using with capital deepening and widening



3.B Theoretical framework

3.B.1 Framework applied to labour or capital-using situations

In this section we show patterns similar to Figure 3.5 but with one or two $\lambda < 0$, i.e. a technical change labour or capital using. The figures 3.B.4 and 3.B.5 feature positive βs.

The figure 3.B.6 is somewhat more baroque since they both represent a case (illustrated by two possible configurations) where one of the two β is negative, i.e. a non-physical situation where one of the two production functions is used negatively.

Figure 3.B.5 – Illustration of a case of capital-using and labour-saving with capital deepening and widening

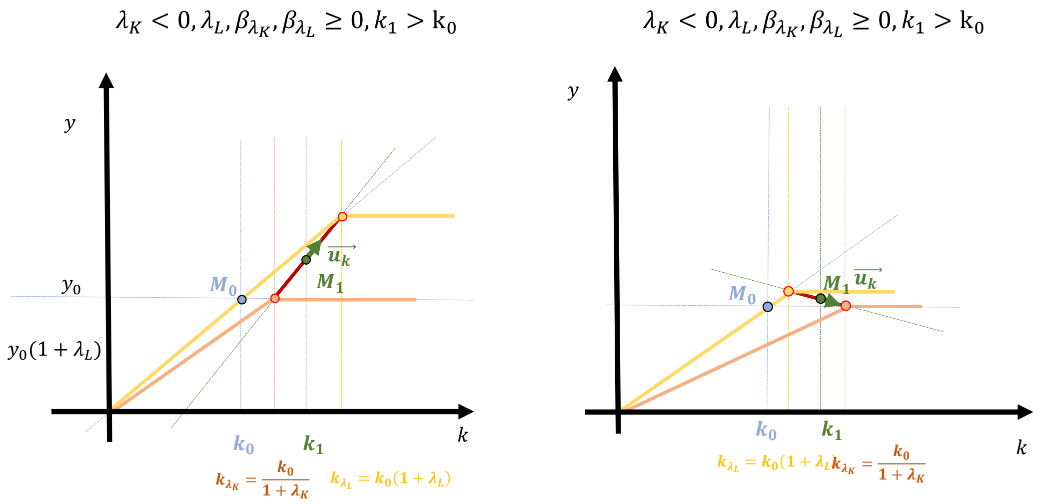


Figure 3.B.6 – Illustration of a case of capital- using and labour-saving with capital deepening and widening (with negative use of the K-saving function)

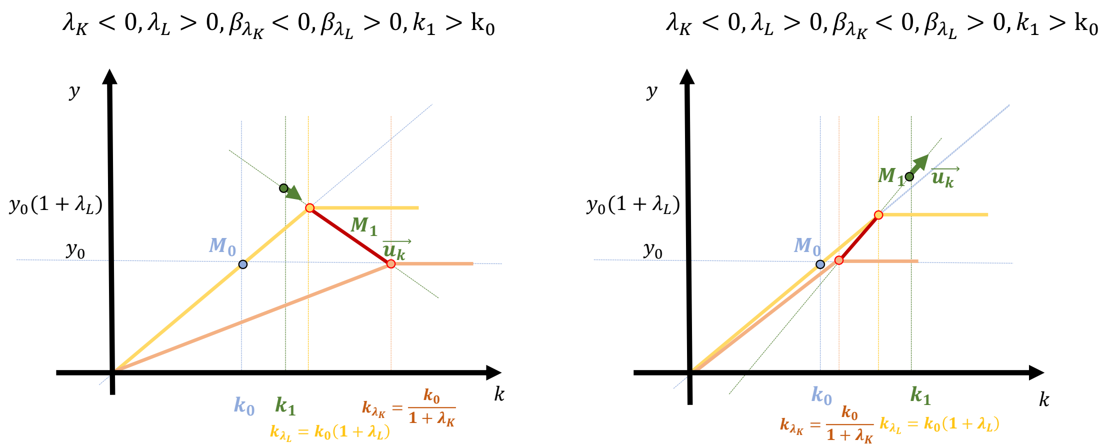


Table 3.C.1 – NAICS industry - KLEMS US database

NAICS	NAICS_Title	NAICS	NAICS_Title
11	Agriculture, forestry, fishery, and hunting	51	Information
111112	Crop & animal production (Farms)	511	Publishing industries, except internet (includes software)
113-115	Forestry, fishing, and related activities	512	Motion picture and sound recording industries
21	Mining	515517	Broadcasting and telecommunications
211	Oil and gas extraction	518519	Data processing, internet publishing, and other information services
212	Mining, except oil and gas	52	Finance and insurance
213	Support activities for mining	52-53	Finance, insurance, real estate, and leasing
22	Utilities	521522	Federal reserve banks, credit intermediation, and related activities
23	Construction	523	Securities, commodity contracts, and other financial investments and related activities
311312	Food and beverage and tobacco products	524	Insurance carriers and related activities
313314	Textile mills and textile product mills	525	Funds, trusts, and other financial vehicles
315316	Apparel and leather and applied products	53	Real estate and rental and leasing
321	Wood products	531	Real estate
322	Paper products	532533	Rental and leasing services and lessors of nonfinancial and intangible assets
323	Printing and related support activities	54	Professional, scientific, and technical services
324	Petroleum and coal products	54-56	Professional and business services
325	Chemical products	54-81	Services
326	Plastics and rubber products	5411	Legal services
327	Nonmetallic mineral products	5412-5414,5416-5419	Miscellaneous professional, scientific, and technical services
331	Primary metal products	5415	Computer systems design and related services
332	Fabricated metal products	55	Management of companies and enterprises
333	Machinery	56	Administrative and waste management services
334	Computer and electronic products	561	Administrative and support services
335	Electrical equipment, appliances, and components	562	Waste management and remediation services
3361-3363	Motor vehicles, bodies and trailers, and parts	61	Educational services
3364-3369	Other transportation equipment	61-62	Educational services, health care, and social assistance
337	Furniture and related products	62	Health care and social assistance
339	Miscellaneous manufacturing	621	Ambulatory health care services
42	Wholesale trade	622623	Hospitals and nursing and residential care facilities
42,44-45	Trade	624	Social assistance
44,45	Retail trade	71	Arts, entertainment, and recreation
48-49	Transportation and warehousing	71-72	Arts, entertainment, recreation, accommodation, and food services
481	Air transportation	711712	Performing arts, spectator sports, museums, and related activities
482	Rail transportation	713	Amusements, gambling, and recreation industries
483	Water transportation	72	Accommodation and food services
484	Truck transportation	721	Accommodation
485	Transit and ground passenger transportation	722	Food services and drinking places
486	Pipeline transportation	81	Other services, except government
487488492	Other transportation and support activities	DM	Durable Manufacturing Sector
493	Warehousing and storage	MN	Manufacturing Sector
		ND	Non-Durable Manufacturing Sector

3.C Description of U.S. factor-saving technical change

3.C.1 KLEMS US NAICS nomenclature

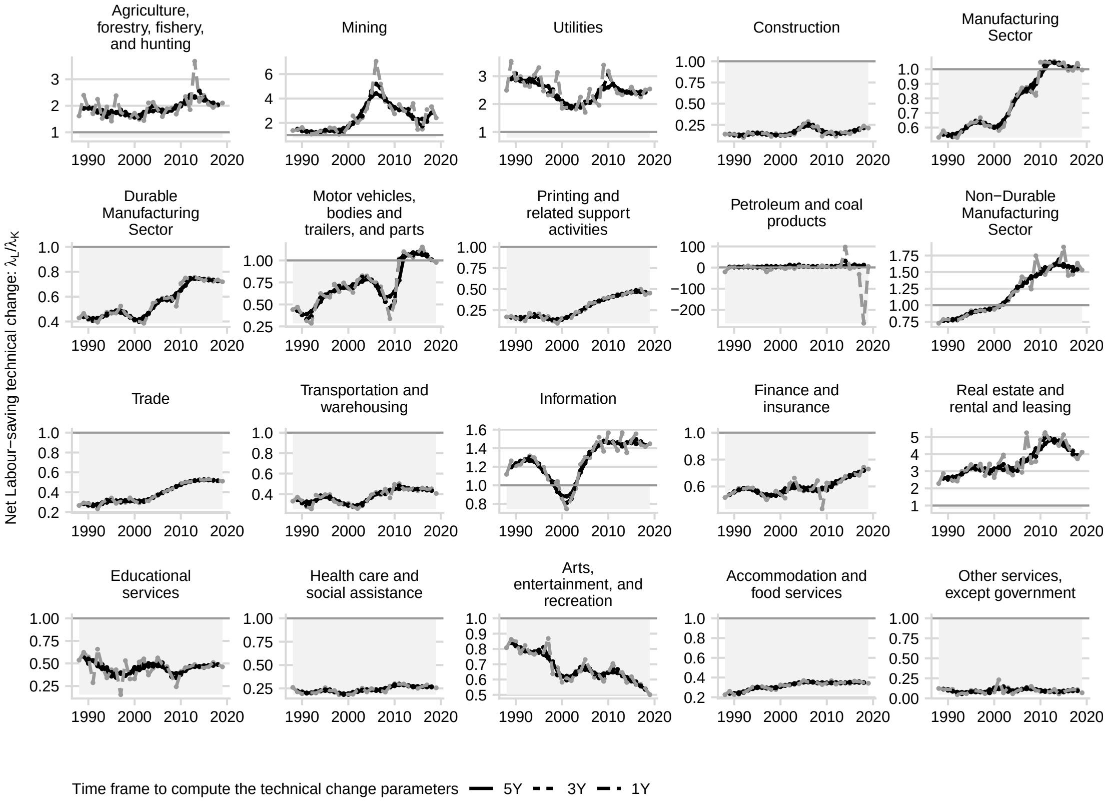
3.C.2 U.S. sectoral net labour-saving technical change

Figure 3.C.7 shows the trends in λ_L/λ_K with different levels of aggregation of data: annual data, data smoothed over a 3-year rolling window and over a 5-year rolling window (as in 4, Figure 3.9). We find that the aggregation has no incidence on the interpretation of trends. We also conclude that the aggregation has no incidence in trends in λ_L et λ_K.

3.C.3 Net labour technical change in the U.S. & Labour share, U.S. 1986-2019

The U.S. industries with the highest λ_L/λ_K ratios are also the sectors where the labour share is the lowest, and thus the most capital-intensive (Figure 3.C.8).

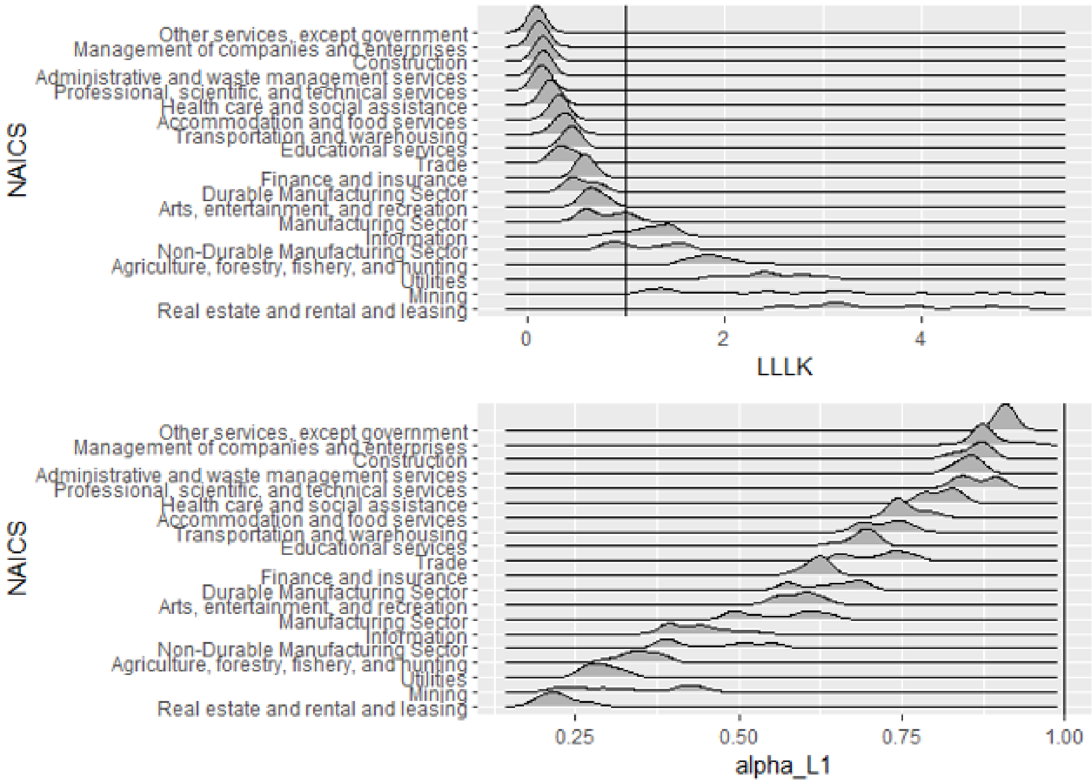
Figure 3.C.7 – Net Labour-saving technical change (λ_L/λ_K) in U.S. industries



3.C.4 Growth accounting in the U.S.

We present here the growth accounting disentangling the contribution of technical change and capital deepening for the U.S. industries detailed in section 4: Printing sector (Figure 3.C.2), Agriculture (3.C.3), Information (3.C.4), Motor vehicles (3.C.5), Petroleum and oil products (3.C.6), Health industry (3.C.7).

Figure 3.C.8 – Distribution of the net direction of technical change λ_L/λ_K (LLLK) per industry in the U.S. (1986-2019) and the distribution of the share of labour (alpha_L1) for the same industries.



Database: KLEMS US 1986-2019

Table 3.C.2 – Growth, substitution, capital and labour-saving technical change accounting. U.S. Printing and related support activities (323). Data are aggregated at the 5Y timespan.

Year	Growth of output per worker	Technical change component	Substitution (capital deepening)
1990-1994	0.007	0.001	0.006
1995-1999	-0.04	-0.04	0.001
2000-2004	0.25	0.19	0.06
2005-2009	0.19	0.12	0.07
2010-2014	0.06	0.008	0.05
2015-2019	0.04	0.06	-0.02

Table 3.C.3 – Growth, substitution, capital and labour-saving technical change accounting. U.S. Agriculture, forestry, fishery, and hunting (11). Data are aggregated at the 5Y timespan.

Year	Growth of output per worker	Technical change component	Substitution (capital deepening)
1990-1994	0.08	0.06	0.02
1995-1999	-0.04	0.03	-0.07
2000-2004	0.27	0.21	0.05
2005-2009	0.02	-0.05	0.07
2010-2014	0.04	0.02	0.01
2015-2019	-0.03	0.02	-0.05

Table 3.C.4 – Growth, substitution, capital and labour-saving technical change accounting. U.S. Information Industry (51). Data are aggregated at the 5Y timespan.

Year	Growth of output per worker	Technical change component	Substitution (capital deepening)
1990-1994	0.07	-0.01	0.08
1995-1999	0.02	-0.02	0.04
2000-2004	0.17	0.00	0.17
2005-2009	0.47	0.19	0.27
2010-2014	0.25	0.03	0.22
2015-2019	0.24	0.05	0.19

Table 3.C.5 – Growth, substitution, capital and labour-saving technical change accounting. U.S. Motor vehicles, bodies and trailers, and parts (3361-3363). Data are aggregated at the 5Y timespan.

Year	Growth of output per worker	Technical change component	Substitution (capital deepening)
1990-1994	-0.03	-0.03	0.00
1995-1999	0.12	0.05	0.07
2000-2004	0.24	0.13	0.11
2005-2009	-0.04	-0.03	-0.01
2010-2014	0.10	-0.04	0.15
2015-2019	0.08	0.10	-0.02

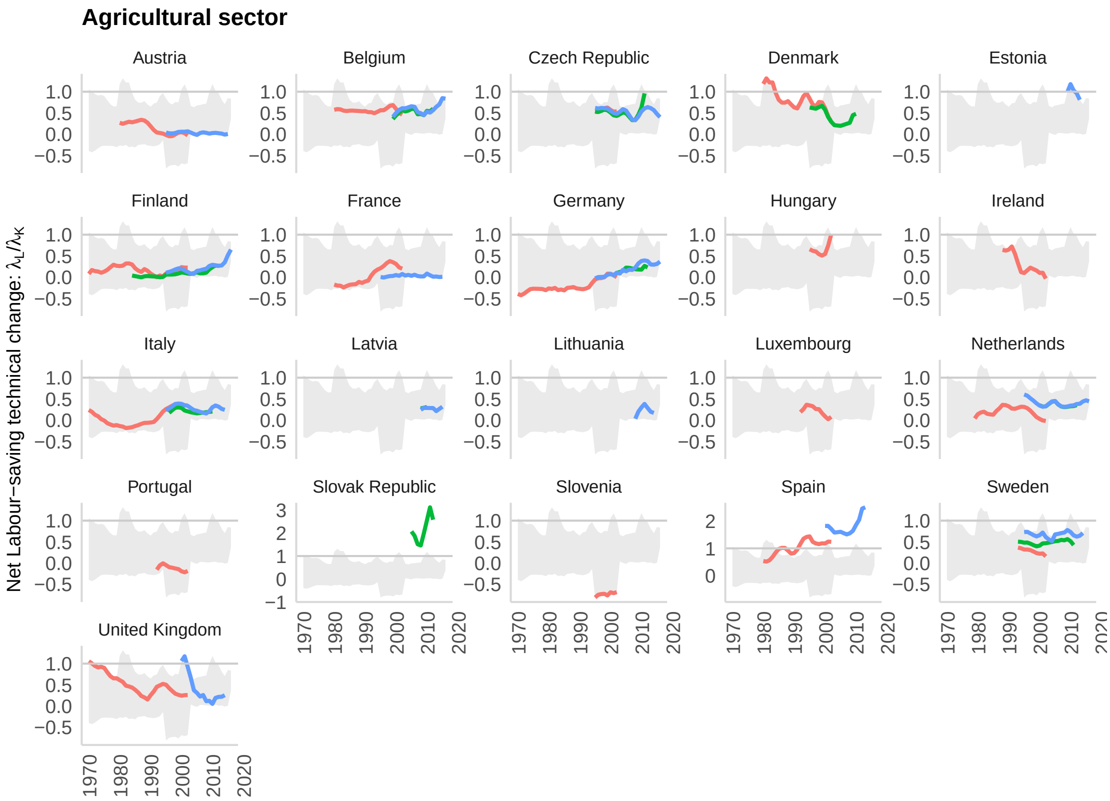
Table 3.C.6 – Growth, substitution, capital and labour-saving technical change accounting. U.S. Petroleum and coal (324). Data are aggregated at the 5Y timespan.

Year	Growth of output per worker	Technical change component	Substitution (capital deepening)
1990-1994	0.20	0.12	0.08
1995-1999	0.36	0.28	0.07
2000-2004	0.30	0.22	0.08
2005-2009	-0.10	-0.21	0.12
2010-2014	-0.20	-0.24	0.04
2015-2019	0.37	0.32	0.05

Table 3.C.7 – Growth, substitution, capital and labour-saving technical change accounting. U.S. Health care and social assistance (62). Data are aggregated at the 5Y timespan.

Year	Growth of output per worker	Technical change component	Substitution (capital deepening)
1990-1994	-0.032	-0.042	0.010
1995-1999	-0.11	-0.12	0.010
2000-2004	0.037	0.025	0.012
2005-2009	0.014	0.008	0.007
2010-2014	0.004	-0.008	0.012
2015-2019	0.021	0.019	0.001

Figure 3.D.9 – Net Labour-saving technical change (λ_L/λ_K) in the Agricultural sector for 21 European countries



Databases: KLEMS v2008 (1970-2005), EU+ KLEMS v2017 (1997-2015) and v2021 (1997-2019)

3.D Description of European factor-saving technical change

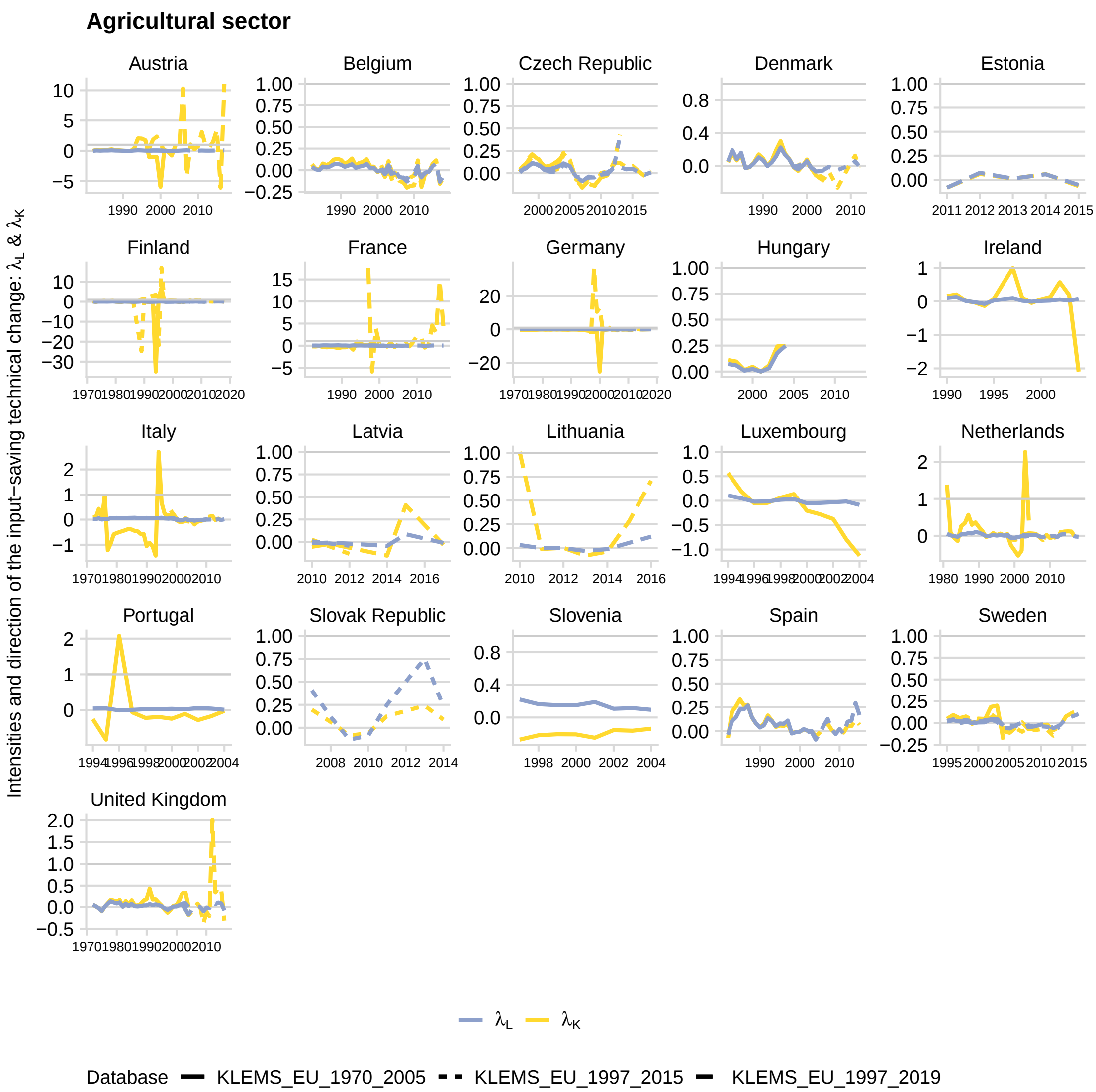
3.D.1 Agricultural and Financial sectors in Europe — net labour-saving trends

We take the example of the agricultural and financial sectors in European countries[48] to show that the three KLEMS databases covering Europe give a consistent picture of the direction of technical change between them. We plot the ratio λ_L/λ_K for the two sectors and show λ_L and λ_K in Agriculture to further illustrate the consistency.

The grey ribbon is the envelope of values for all countries concerned (minus Spain and Slovakia for the Agricultural sector, see Figure 3.10 in section 4.2).

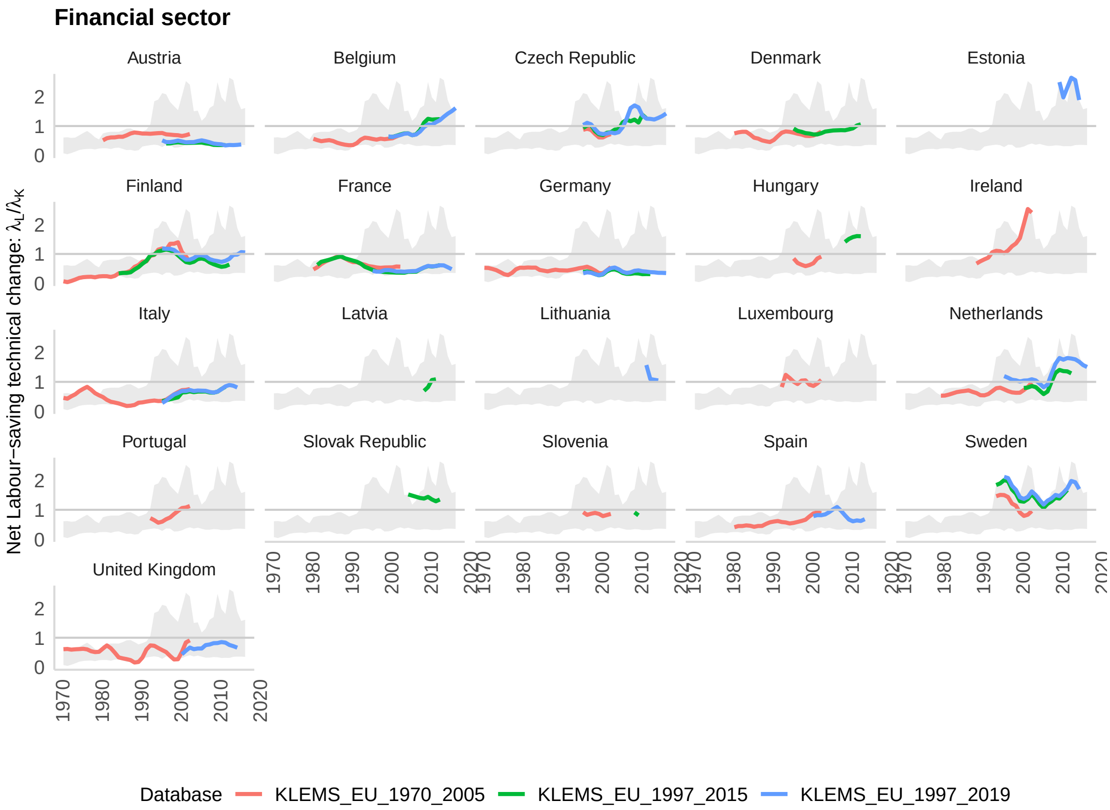
[48] SIC: "J-FINANCIAL INTERMEDIATION" and NACE: "K-Financial and insurance activities".

Figure 3.D.10 – Labour and capital saving technical change in in the Agricultural sector for 21 European countries



Databases: KLEMS v2008 (1970-2005), EU+ KLEMS v2017 (1997-2015) and v2021 (1997-2019)

Figure 3.D.11 – Net Labour-saving technical change (λ_L/λ_K) in the Financial sector for 21 European countries

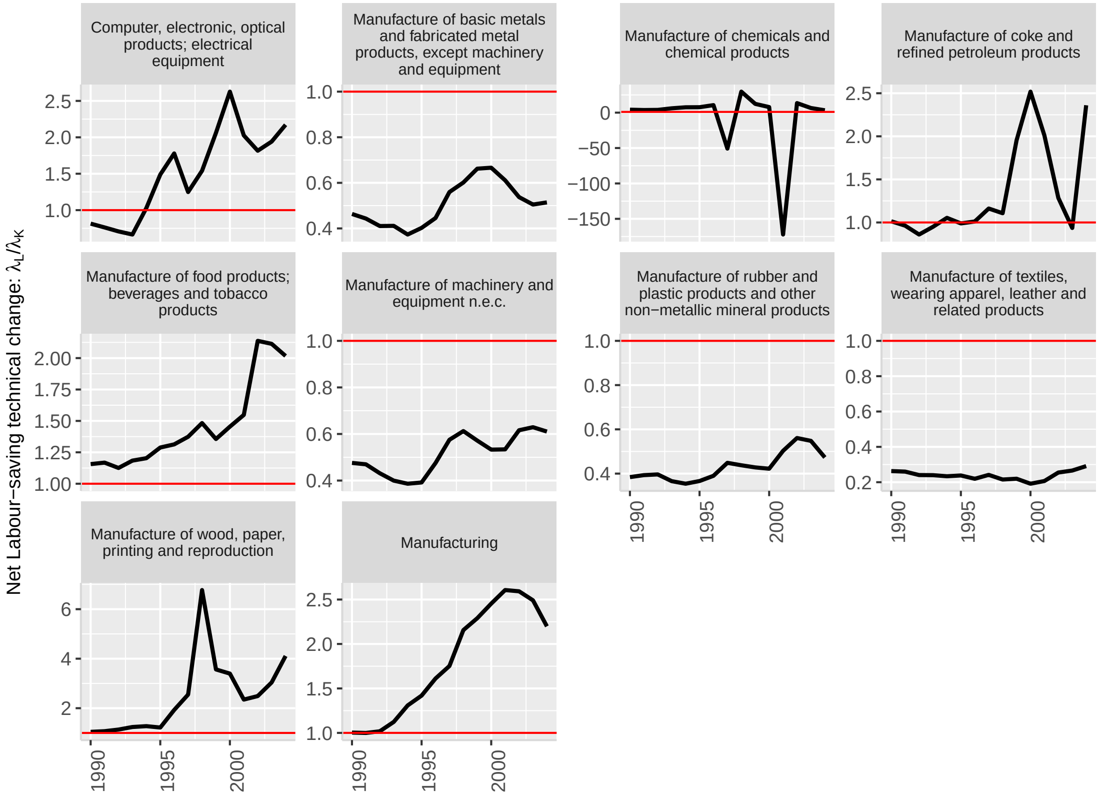


Databases: KLEMS v2008 (1970-2005), EU+ KLEMS v2017 (1997-2015) and v2021 (1997-2019)

3.D.2 Manufacturing sector in Ireland

We detail the industries aggregated under the "Manufacturing sector" label in Ireland. Aggregate net-labour saving performance is driven by new high technologies.

Figure 3.D.12 – Net Labour-saving technical change (λ_L/λ_K) in Ireland



Database: EU+ KLEMS v2017 (1997-2015)

3.E Testing for Hicks's hypothesis

3.E.1 $\lambda \sim \Delta r + \Delta w$ — Estimating the relationship between the intensity of technical change and prices

We refine the results discussed in section 5.7.

The results in Figure 3.16 are broken down by database to show our results are not concentrated on one database. Note that we find no significant results for the U.S. in the KLEMS US NAICS (1986-2019) database .

On the figure 3.E.14 we see the 5 points constrained by the scale of the figure 3.16. Of these 5 points, 3 confirm the Hicks's hypothesis. Points 15 and 16 show a very negative a_w^K coefficient. Point 3, a very negative coefficient for a_r^L. Points 1 and 30 contradicts Hicks's hypothesis: point 1 shows a very negative coefficient for the coefficient a_w^K and point 30 shows a very positive a_w^K, but of such a magnitude that we can infer a measurement error.

Figure 3.E.13 – Estimation of the relationship between the relative intensity of technical change (λ_L/λ_K) and price variation ($\Delta w, \Delta r$). Sample: KLEMS EU+, 1970-2005, 1996-2019, KLEMS US 1986-2019. Décomposition par base de données.

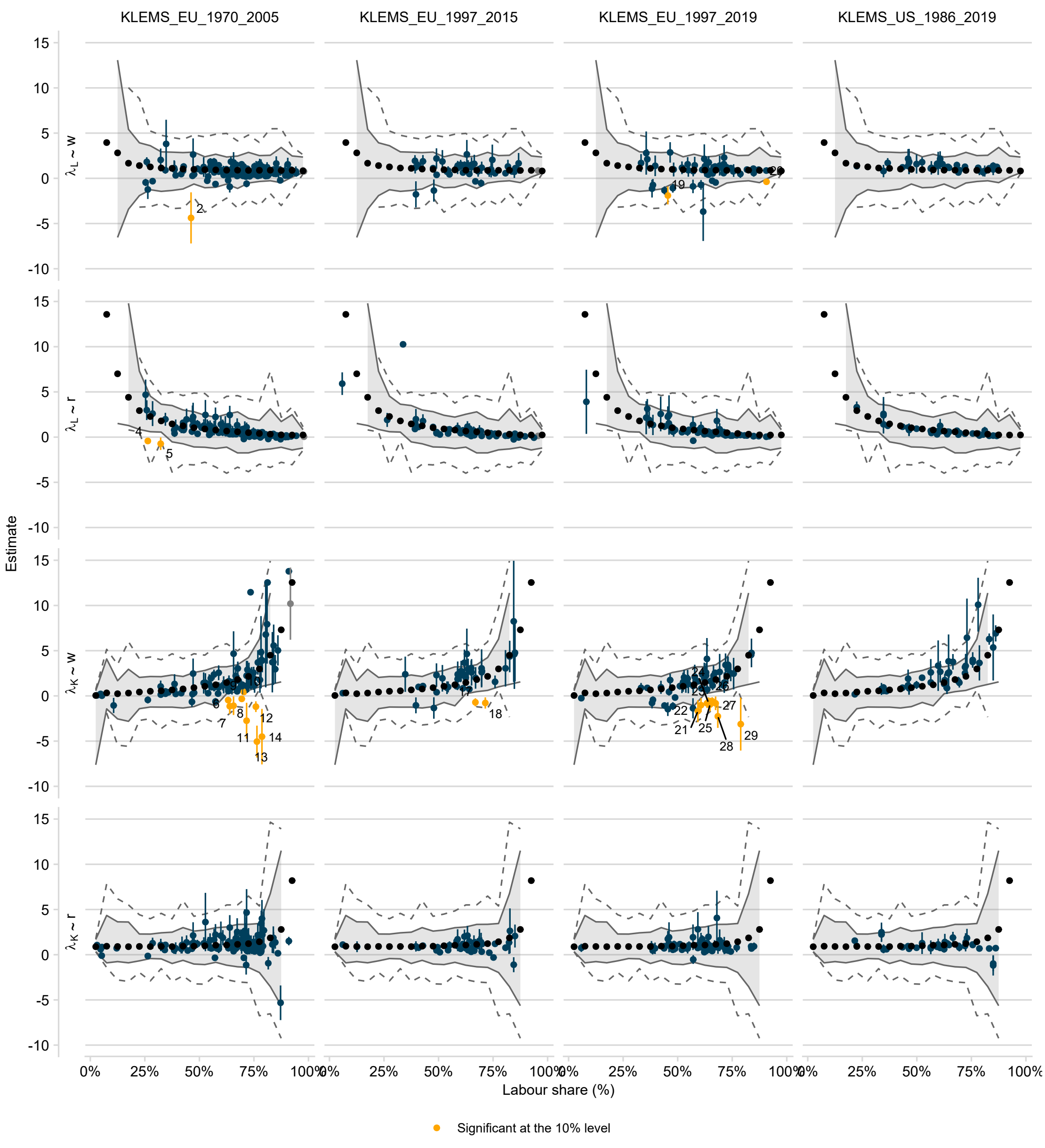


Figure 3.E.14 – Estimation of the relationship between the intensity of technical change (λ_L, λ_K) and price variations ($\Delta w + \Delta r$) on a larger scale.

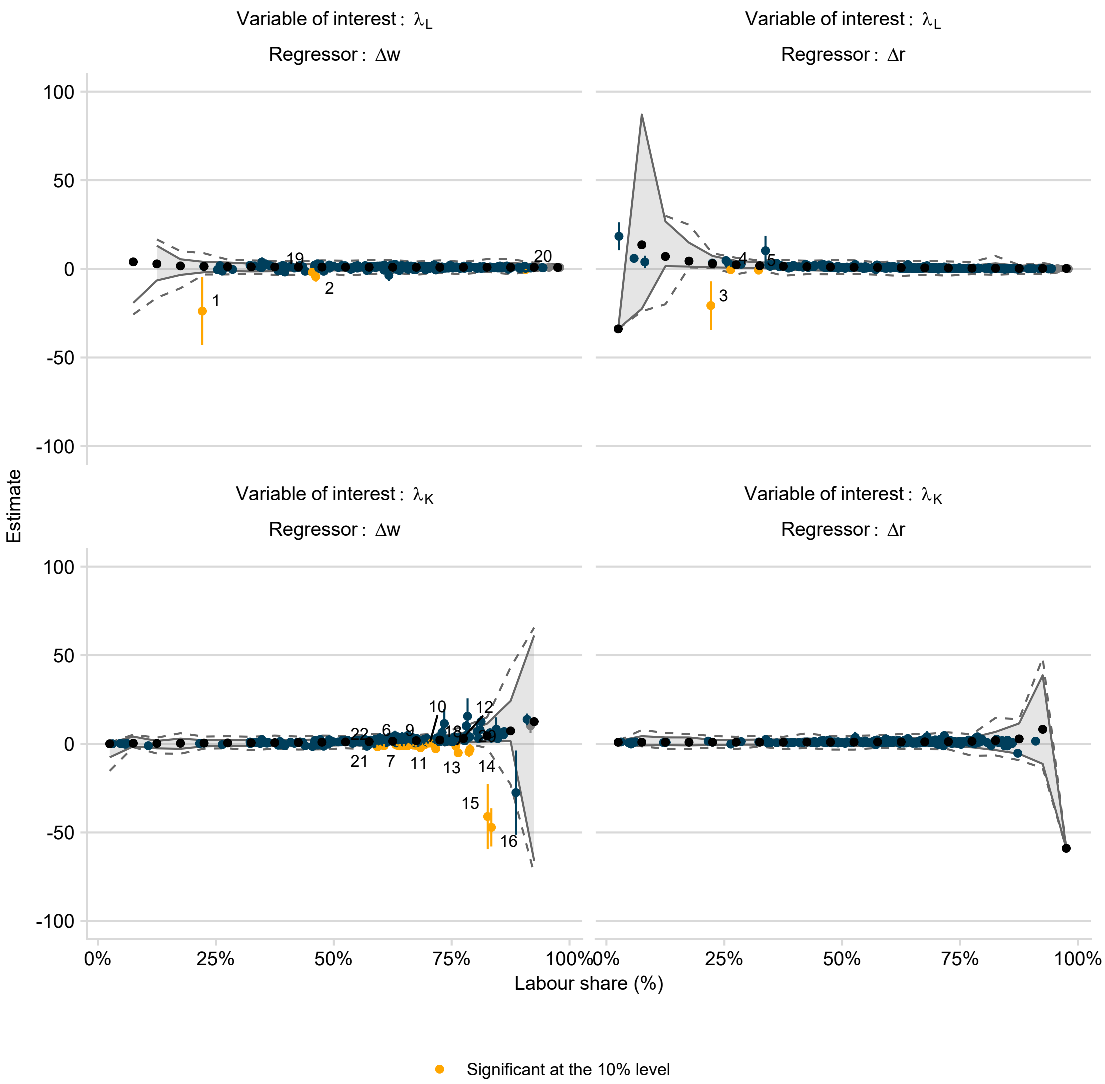
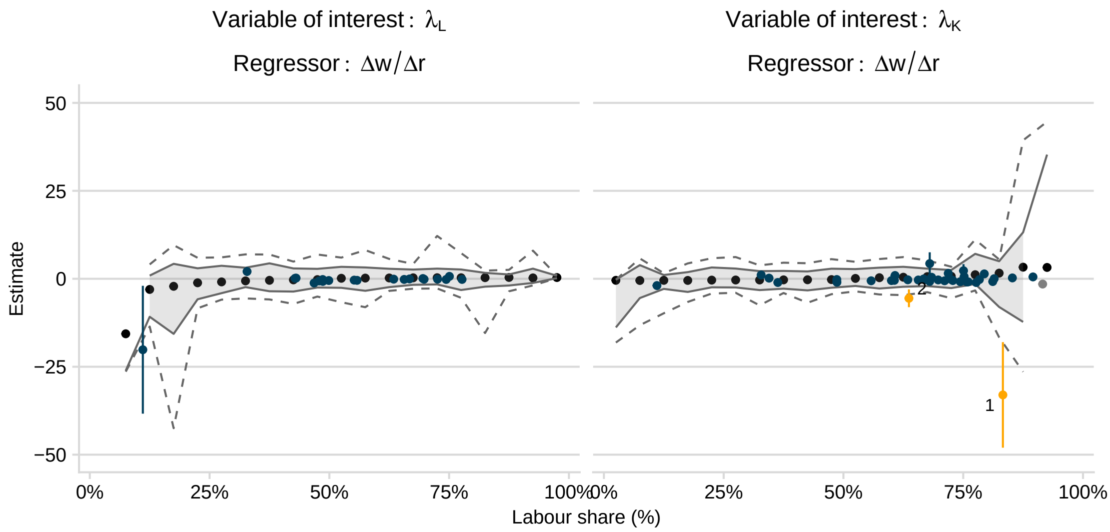


Figure 3.E.15 – Estimation of the relationship between the relative intensity of technical change (λ_L, λ_K) and price variation $(\Delta w/r)$. Sample: KLEMS EU, 1970-2005, 1996-2019.



3.E.2 $\lambda \sim \Delta w/r$ — Estimating the relationship between the intensity of technical change and relative prices

Estimate of equation (3.19) $\lambda \sim \Delta \frac{w}{r}$ already discussed briefly in section 5.6.

The estimation of λ on the variations of the relative prices of the inputs $(\Delta w/r)$ from (3.19) gives very few significant results. Only two points differ from the estimations on randomly generated data (Table 3.E.8). These two points show estimates of $a^K_{w/r}$ coefficients significantly negative (Figure 3.E.15). It points in the direction of Hicks's hypothesis where an increase in the relative cost of labour leads to capital-using, that is labour-saving, technical change. Note that there are fewer significant results even on randomly generated data than for other specifications.

Table 3.E.8 – Industries for which the relationship between the intensity of technical change $(\lambda_{L,K})$ on relative price variations $(\Delta \frac{w}{r})$ is significantly different from the relationship estimated on randomly generated series

Legend	Scope	Country	Industry code	Industry
1	KLEMS EU+ v2008	Finland	AtB	Agriculture, hunting, forestry and fishing
2	KLEMS EU+ v2017	Slovak Republic	62-63	IT and other information services

3.E.3 Selected industries — Regressions tables

We include the regressions of the sectors we distinguish in Table 3.7: equation 3.20. What we expect is to have a positive coefficient between λ_L and Δw, negative with Δr and vice versa on λ_K.

This is the case for a large number of sectors (note that this is the case for a large number of sectors, see the graphs, but here we are looking at those that fall outside the 90% confidence interval of randomised data regressions).

Notice that in a number of industries, there is a negative relationship between wage growth and labour-saving technical change which is opposite to the intuition of the Hicks's hypothesis.

Table 3.E.9 – United Kingdom — Non metallic mineral (left) & Germany — Manufacture of computer, electronic and optical products (right)

	UK 26 — 1970-2005	
	λ_K	λ_L
	(1)	(2)
Δw	-4.917^***	0.032
	(0.973)	(0.126)
Δr	1.058^**	0.182^***
	(0.495)	(0.064)
outlier_1986	0.492	0.149^**
	(0.559)	(0.073)
Weak instruments (Δw)	0	0
Weak instruments (Δr)	0.01335521	0.01335521
Wu-Hausman	6.116e-05	0.00013292
Sargan	0.51079609	0.65046118
Observations	35	35
R^2	0.540	0.372
Adjusted R^2	0.497	0.313
Residual Std. Error (df = 32)	0.540	0.070
Note:	*p<0.1; **p<0.05; ***p<0.01	

	DE C26 — 1997-2019	
	λ_K	λ_L
	(1)	(2)
Δ_w	-1.791^**	-0.986^*
	(0.838)	(0.509)
Δr	2.985^**	1.697^*
	(1.345)	(0.818)
outlier_2007	0.231	0.340
	(0.347)	(0.211)
Weak instruments (Δw)	0	0
Weak instruments (Δr)	0.00143811	0.00143811
Wu-Hausman	0.0647089	0.24511706
Sargan	0.41580352	0.28322494
Observations	23	23
R^2	0.118	0.347
Adjusted R^2	-0.015	0.249
Residual Std. Error (df = 20)	0.296	0.180
Note:	*p<0.1; **p<0.05; ***p<0.01	

3.F Forecast labour share

3.F.1 Estimation of the elasticity of substitution

Figure 3.F.16 shows the estimates of the elasticity of substitution between capital and labour using the three specification from equations (3.32), (3.33) and (3.34).

3.F.2 Estimation of the drivers of βs

We report the estimations of the βs prior to the forecast step for three sectors: Agriculture (table 3.F.17), Manufacturing (table 3.F.18), Paper products (table 3.F.19) and Finance (table 3.F.20).

Table 3.E.10 – Germany — Information and communication (left) & EU11 — Chemicals; basic pharmaceutical products (right)

	DE J — 1997-2019	
	λ_K	λ_L
	(1)	(2)
Δw	-0.699	-0.453
	(0.522)	(0.351)
Δr	1.030	0.672
	(0.701)	(0.471)
outlier_1998	0.094	0.139
	(0.142)	(0.095)
outlier_2003	0.048	0.026
	(0.175)	(0.118)
Weak instruments (Δw)	0	0
Weak instruments (Δr)	0.00028142	0.00028142
Wu-Hausman	0.47828	0.67277387
Sargan	0.02245147	0.02896701
Observations	24	24
R^2	0.511	0.584
Adjusted R^2	0.413	0.501
Residual Std. Error (df = 20)	0.096	0.064
Note:	*p<0.1; **p<0.05; ***p<0.01	

	EU11_C20-C21 — 1997-2019	
	λ_K	λ_L
	(1)	(2)
Δ_w	-1.466^***	-1.899^***
	(0.387)	(0.506)
Δr	1.743^***	2.253^***
	(0.446)	(0.584)
outlier_2017	-0.144^**	-0.180^**
	(0.054)	(0.071)
outlier_2018	-0.321^***	-0.404^***
	(0.055)	(0.072)
Weak instruments (Δ_w)	3e-07	3e-07
Weak instruments (Δr)	2.069e-05	2.069e-05
Wu-Hausman	0.00084095	0.00343526
Sargan	0.90260979	0.84623409
Observations	10	10
R^2	0.909	0.904
Adjusted R^2	0.849	0.840
Residual Std. Error (df = 6)	0.053	0.070
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 3.E.11 – Germany — Manufacture of motor vehicles, trailers, semi-trailers and of other transport equipment (left) & Italy — Manufacture of wood, paper, printing and reproduction (right)

	DE C29-C30 — 1997-2019	
	λ_K	λ_L
	(1)	(2)
Δw	-0.789^***	-0.275^*
	(0.265)	(0.142)
Δr	1.271^***	0.477^***
	(0.291)	(0.156)
outlier_2010	0.920^***	0.578^***
	(0.187)	(0.101)
Weak instruments (Δw)	0	0
Weak instruments (Δr)	0.00050743	0.00050743
Wu-Hausman	0.04329589	0.03428827
Sargan	0.33290751	0.31503225
Observations	23	23
R^2	0.925	0.917
Adjusted R^2	0.913	0.904
Residual Std. Error (df = 20)	0.114	0.061
Note:	*p<0.1; **p<0.05; ***p<0.01	

	IT C16-C18—1997-2019	
	λ_K	λ_L
	(1)	(2)
Δw	-1.268^**	-0.657^**
	(0.574)	(0.258)
Δr	-0.064	-0.038
	(0.283)	(0.127)
outlier_2001	0.251^*	0.164^***
	(0.122)	(0.055)
Weak instruments (Δw)	2.9e-07	2.9e-07
Weak instruments (Δr)	0.00509535	0.00509535
Wu-Hausman	0.00014155	6.742e-05
Sargan	0.72671123	0.72375921
Observations	22	22
R^2	0.198	0.381
Adjusted R^2	0.071	0.283
Residual Std. Error (df = 19)	0.095	0.043
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 3.E.12 – EU11 C (left) & Italy (right) — Manufacturing

	EU11 C — 1997-2019	
	λ_K	λ_L
	(1)	(2)
Δw	-0.958	-0.408
	(0.538)	(0.340)
Δr	1.154	0.501
	(0.711)	(0.449)
outlier_2018	-0.432^***	-0.345^***
	(0.117)	(0.074)
Weak instruments (Δw)	0	0
Weak instruments (Δr)	0.0001854	0.0001854
Wu-Hausman	0.02813056	0.04241401
Sargan	0.8719738	0.92930791
Observations	10	10
R^2	0.830	0.854
Adjusted R^2	0.757	0.791
Residual Std. Error (df = 7)	0.100	0.063
Note:	*p<0.1; **p<0.05; ***p<0.01	

	IT C — 1997-2019	
	λ_K	λ_L
	(1)	(2)
Δw	-0.581^**	-0.261^**
	(0.229)	(0.109)
Δr	0.403^***	0.186^***
	(0.136)	(0.065)
outlier_2018	-1.113^***	-1.045^***
	(0.112)	(0.053)
Weak instruments (Δw)	0	0
Weak instruments (Δr)	0	0
Wu-Hausman	0.00594091	0.00370386
Sargan	0.80557705	0.85575306
Observations	23	23
R^2	0.929	0.982
Adjusted R^2	0.919	0.979
Residual Std. Error (df = 20)	0.064	0.030
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 3.E.13 – Austria (left) & Finland (right) — Rubber and plastics

	AUT 25 — 1970-2005	
	λ_K	λ_L
	(1)	(2)
Δw	-2.757	-0.471^**
	(1.635)	(0.188)
Δr	2.560^**	0.427^***
	(1.172)	(0.135)
outlier_1991	-0.100	0.042
	(0.648)	(0.075)
Weak instruments (Δw)	0	0
Weak instruments (Δr)	0.00026556	0.00026556
Wu-Hausman	0.55633215	0.2650678
Sargan	0.37916596	0.15932904
Observations	24	24
R^2	0.483	0.607
Adjusted R^2	0.409	0.550
Residual Std. Error (df = 21)	0.502	0.058
Note:	*p<0.1; **p<0.05; ***p<0.01	

	FIN 25 — 1970-2005	
	λ_K	λ_L
	(1)	(2)
Δw	-1.085^**	-0.218
	(0.523)	(0.145)
Δr	-0.093	0.169
	(1.191)	(0.330)
outlier_1985	1.611^***	0.368^***
	(0.394)	(0.109)
Weak instruments (Δw)	0	0
Weak instruments (Δr)	0.23674957	0.23674957
Wu-Hausman	0.00753165	0.00245374
Sargan	0.60793417	0.53987168
Observations	35	35
R^2	0.402	0.488
Adjusted R^2	0.346	0.440
Residual Std. Error (df = 32)	0.313	0.087
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 3.E.14 – Austria — Machinery (left) & Japan — Real estate, renting and business activities (right)

	AUT 29 — 1970-2005	
	λ_K	λ_L
	(1)	(2)
Δw	-1.555^***	-0.263^**
	(0.329)	(0.097)
Δr	2.311^***	0.671^***
	(0.688)	(0.204)
outlier_1984	0.530	0.208^*
	(0.374)	(0.111)
outlier_2000	-0.321	-0.063
	(0.336)	(0.099)
Weak instruments (Δw)	0	0
Weak instruments (Δr)	0.05817632	0.05817632
Wu-Hausman	0.25844514	0.07164256
Sargan	0.00753582	0.0969291
Observations	25	25
R^2	0.727	0.513
Adjusted R^2	0.675	0.421
Residual Std. Error (df = 21)	0.208	0.062
Note:	*p<0.1; **p<0.05; ***p<0.01	

	JPN K — 1970-2005	
	λ_K	λ_L
	(1)	(2)
Δw	-0.443^**	-1.232^**
	(0.203)	(0.542)
Δr	-0.145^***	-0.431^***
	(0.047)	(0.126)
outlier_1975	-0.298^***	-0.904^***
	(0.061)	(0.164)
Weak instruments (Δw)	2e-08	2e-08
Weak instruments (Δr)	0	0
Wu-Hausman	0.00384644	0.00192127
Sargan	0.23523188	0.20843939
Observations	32	32
R^2	0.407	0.513
Adjusted R^2	0.345	0.463
Residual Std. Error (df = 29)	0.041	0.109
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table 3.E.15 – Austria (left) & France (right): Food, beverages and tobacco

	AUT 15t16 — 1970-2005	
	λ_K	λ_L
	(1)	(2)
Δw	-2.805^**	-0.866^**
	(1.348)	(0.389)
Δr	4.770^**	1.545^**
	(1.969)	(0.569)
Weak instruments (Δw)	0	0
Weak instruments (Δr)	0.00678501	0.00678501
Wu-Hausman	0.00069403	0.00492665
Sargan	0.37899404	0.32349132
Observations	25	25
R^2	-0.096	0.107
Adjusted R^2	-0.191	0.030
Residual Std. Error (df = 23)	0.277	0.080
Note:	*p<0.1; **p<0.05; ***p<0.01	

	FRA 15t16 — 1970-2005	
	λ_K	λ_L
	(1)	(2)
Δw	-0.326^**	-0.105
	(0.145)	(0.069)
Δr	0.624	0.308
	(0.797)	(0.380)
outlier_1985	0.093	0.066
	(0.161)	(0.077)
outlier_2001	-0.106	-0.055
	(0.100)	(0.048)
Weak instruments (Δw)	0	0
Weak instruments (Δr)	0.60809982	0.60809982
Wu-Hausman	0.00887549	0.00730707
Sargan	0.50118268	0.49648479
Observations	25	25
R^2	0.516	0.566
Adjusted R^2	0.424	0.483
Residual Std. Error (df = 21)	0.072	0.034
Note:	*p<0.1; **p<0.05; ***p<0.01	

Figure 3.F.16 – Sigma estimates

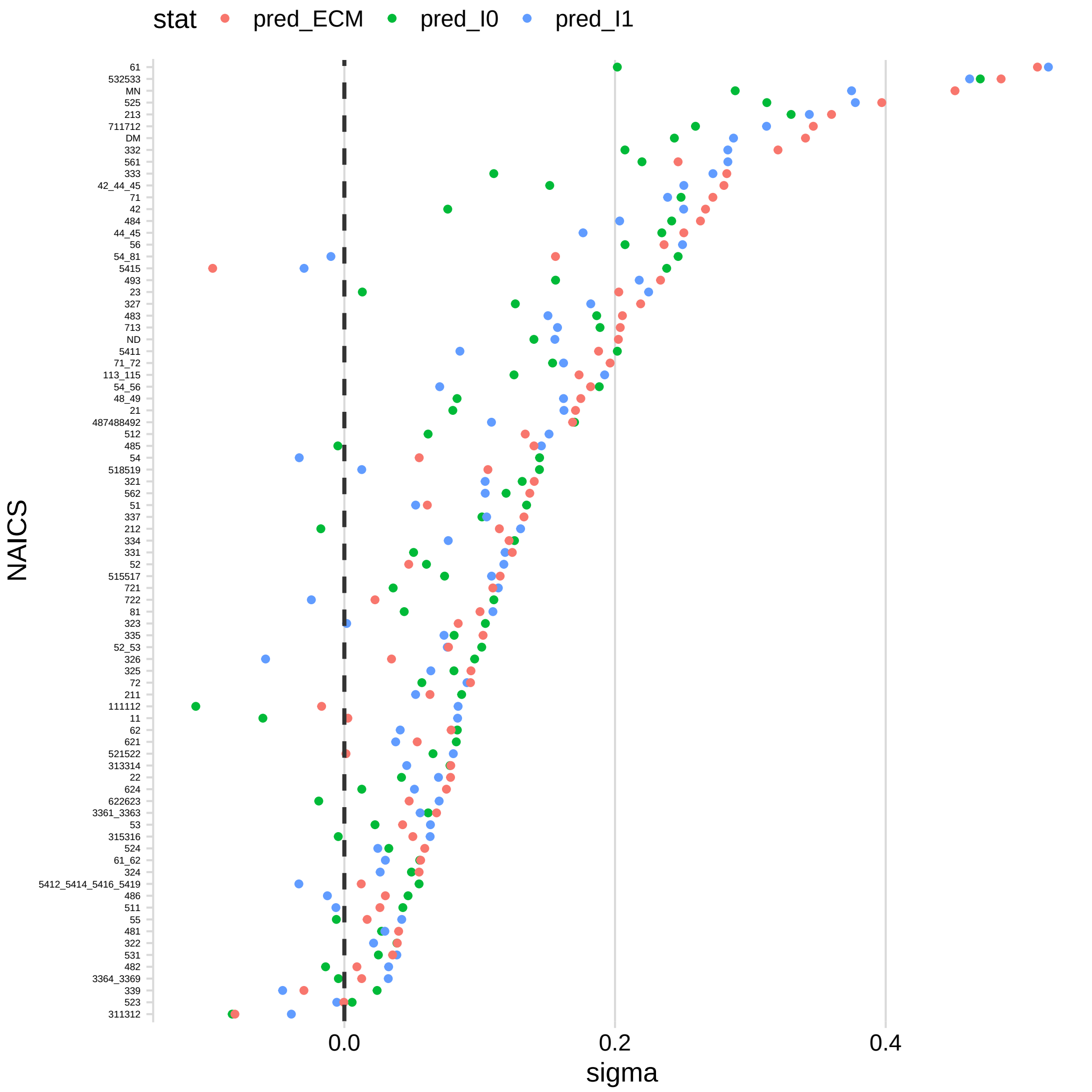


Table 3.E.16 – USA-SIC E — Electricity, gas and water supply (left) & SVK K — Real estate, renting and business activities — Slovak Republic (right)

	USA-SIC E — 1970-2005	
	λ_K	λ_L
	(1)	(2)
Δw	1.109^***	2.122^***
	(0.365)	(0.692)
Δr	-0.373^*	-0.741^**
	(0.190)	(0.359)
outlier_1974	-0.185^***	-0.296^**
	(0.067)	(0.127)
outlier_1988	0.033	0.109
	(0.068)	(0.129)
Weak instruments (Δw)	0.00480378	0.00480378
Weak instruments (Δr)	0	0
Wu-Hausman	4e-08	0
Sargan	0.73643771	0.84072331
Observations	35	35
R^2	0.144	0.157
Adjusted R^2	0.033	0.048
Residual Std. Error (df = 31)	0.061	0.116
Note:		*p<0.1; **p<0.05; ***p<0.01

	SVN K — 1970-2005	
	λ_K	λ_L
	(1)	(2)
Δw	-3.947^**	-4.377^**
	(1.336)	(1.443)
Δr	-0.249	-0.297
	(0.182)	(0.196)
outlier_2001	0.423^**	0.466^**
	(0.150)	(0.162)
outlier_2003	-0.429^**	-0.471^**
	(0.121)	(0.131)
Weak instruments (Δw)	0.19513872	0.19513872
Weak instruments (Δr)	8.335e-05	8.335e-05
Wu-Hausman	0.05581767	0.0368935
Sargan	0.29862767	0.36123232
Observations	10	10
R^2	0.565	0.572
Adjusted R^2	0.275	0.286
Residual Std. Error (df = 6)	0.060	0.064
Note:		*p<0.1; **p<0.05; ***p<0.01

3.F.3 Forecast of the labour share — testing set

We have restricted the sample of industries to the industries we can link to an estimate of the elasticities of substitution as estimated by Young (2013). Figure 3.F.17 reproduces the trend of figure 3.20: our framework is better than all the others models for some industries, but more importantly, it is seldom out of touch.

We have plotted the forecast of the bias of technical change for the four industries (Agriculture, Manufacturing, Finance and paper products) using the three specifications detailed in (3.30),(3.28),(3.29) (Figure 3.F.18).

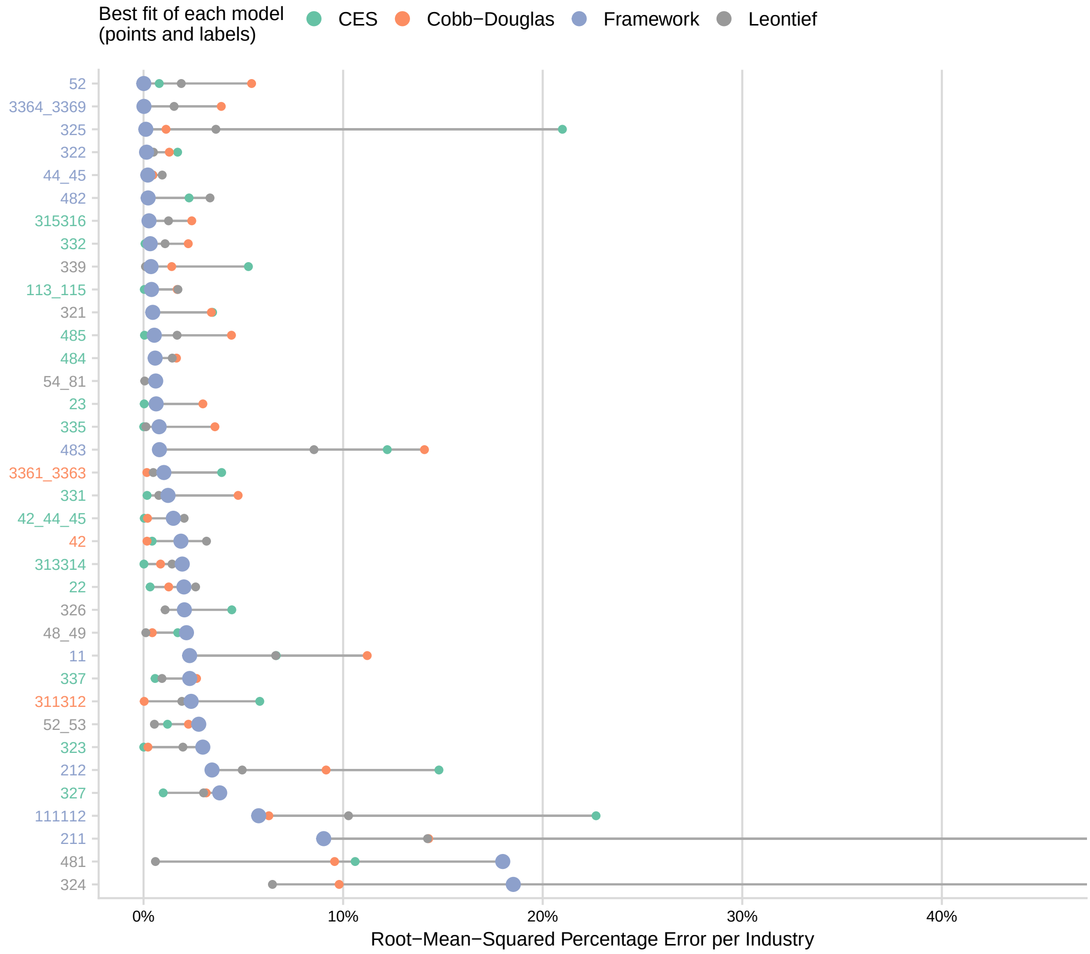
3.F.4 Sensitivity to start year and length of the testing set

We plot the forecast of the labour share for four industries (Agriculture, Manufacturing, Finance and paper products) varying the length of the training set, and thus the starting year of the forecast (Figure 3.F.19, 3.21, 3.F.20, 3.F.21).

3.F.5 Long-term 2030 Forecast

We use our framework to forecast the bias of technical change up to 2030 (Figure 3.F.22), along with the forecast of the labour-share (Figure 3.22 using the prices forecasted as in figure 3.F.23).

Figure 3.F.17 – Forecast of the labour-share per industry and error per category of model



Note: The industries represented are the one for which an estimation of the elasticities of substitution between capital and labour is available in Young (2013). Only the best fit of each model category is retained. The colour of the industry code on the vertical axis indicates the best model for that industry.

Table 3.F.17 – U.S. — 1986-2019 — Agricultural sector

	Dependent variable:					
		β_L			β_K	
	(1)	(2)	(3)	(4)	(5)	(6)
λ_K	−6.460		2.446	−13.015**		−2.097
	(5.398)		(4.598)	(5.398)		(4.913)
λ_L	3.652		−1.172	7.140**		1.459
	(2.725)		(2.295)	(2.726)		(2.453)
$\beta_L(t-1)$		0.541***	0.543***		0.474***	0.429***
		(0.110)	(0.120)		(0.121)	(0.128)
$\beta_K(t-1)$		0.403***	0.442***		0.568***	0.527***
		(0.116)	(0.142)		(0.127)	(0.151)
outlier_1998	2.175***	1.660***	1.646***	−1.168*	−1.672***	−1.630***
	(0.601)	(0.403)	(0.423)	(0.601)	(0.444)	(0.452)
Observations	25	24	24	25	24	24
R^2	0.411	0.758	0.762	0.345	0.665	0.688
Adjusted R^2	0.331	0.723	0.699	0.256	0.617	0.606
Note:						*p<0.1; **p<0.05; ***p<0.01

Note: Columns 1-4, 2-5, 3-6 correspond respectively to the equations (3.29), (3.29), (3.30).

3.G Energy saving technical change

Table 3.F.18 – U.S. — 1986-2019 — Manufacturing Sector

	Dependent variable:					
	β_L			β_K		
	(1)	(2)	(3)	(4)	(5)	(6)
λ_K	37.655***		16.232	5.586		−16.163
	(9.447)		(10.601)	(8.916)		(10.406)
λ_L	−42.210***		−16.484	−9.694		16.910
	(12.525)		(13.441)	(11.821)		(13.194)
$\beta_L(t-1)$		0.749***	0.548***		0.251*	0.445***
		(0.126)	(0.154)		(0.122)	(0.152)
$\beta_K(t-1)$		0.647***	0.465***		0.352**	0.528***
		(0.137)	(0.159)		(0.132)	(0.156)
outlier_1990	8.618***	8.011***	8.165***	−7.693***	−8.030***	−8.181***
	(0.682)	(0.612)	(0.564)	(0.643)	(0.591)	(0.554)
outlier_2004	−4.171***	−4.925***	−4.720***	5.174***	4.908***	4.711***
	(0.681)	(0.611)	(0.566)	(0.643)	(0.590)	(0.556)
Observations	25	24	24	25	24	24
R^2	0.914	0.937	0.953	0.909	0.930	0.946
Adjusted R^2	0.898	0.924	0.937	0.891	0.916	0.928
Note:					*p<0.1; **p<0.05; ***p<0.01	

Note: Columns 1-4, 2-5, 3-6 correspond respectively to the equations (3.29), (3.29), (3.30).

Table 3.F.19 – U.S. — 1986-2019 — Paper industry

	Dependent variable:					
		β_L			β_K	
	(1)	(2)	(3)	(4)	(5)	(6)
λ_K	0.441		2.000	−3.263		−1.421
	(4.595)		(3.214)	(4.407)		(3.077)
λ_L	0.268		−1.739	3.973		1.682
	(5.442)		(3.737)	(5.220)		(3.578)
$\beta_L(t-1)$		0.489***	0.502***		0.499***	0.491***
		(0.086)	(0.089)		(0.080)	(0.085)
$\beta_K(t-1)$		0.524***	0.510***		0.482***	0.485***
		(0.093)	(0.095)		(0.086)	(0.091)
outlier_1991	−1.281*	−1.796***	−1.776***	2.286***	1.818***	1.814***
	(0.639)	(0.400)	(0.407)	(0.613)	(0.372)	(0.390)
outlier_2000	7.181***	6.648***	6.644***	−6.204***	−6.726***	−6.722***
	(0.639)	(0.400)	(0.408)	(0.613)	(0.372)	(0.390)
Observations	25	24	24	25	24	24
R^2	0.862	0.951	0.954	0.848	0.949	0.950
Adjusted R^2	0.836	0.941	0.939	0.819	0.939	0.933
Note:						*p<0.1; **p<0.05; ***p<0.01

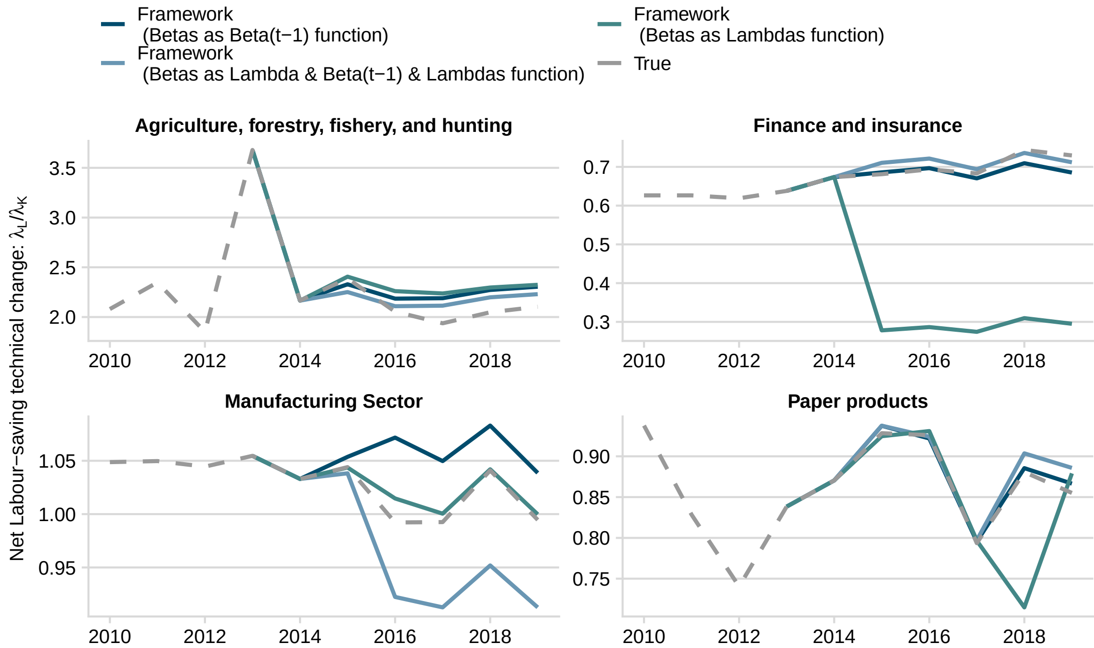
Note: Columns 1-4, 2-5, 3-6 correspond respectively to the equations (3.29), (3.29), (3.30).

Table 3.F.20 – U.S. — 1986-2019 — Financial Sector

	Dependent variable:					
		β_L			β_K	
	(1)	(2)	(3)	(4)	(5)	(6)
λ_K	1.456		−2.055	4.435		2.666
	(5.906)		(4.247)	(4.947)		(4.246)
λ_L	0.071		5.828	−9.444		−6.275
	(11.980)		(8.574)	(10.036)		(8.572)
$\beta_L(t-1)$		0.686***	0.673***		0.311**	0.308*
		(0.143)	(0.148)		(0.140)	(0.148)
$\beta_K(t-1)$		0.708***	0.692***		0.292**	0.292*
		(0.137)	(0.142)		(0.134)	(0.142)
outlier_1990	−12.896***	−13.653***	−13.628***	13.927***	13.651***	13.644***
	(0.971)	(0.696)	(0.702)	(0.814)	(0.682)	(0.702)
Observations	25	24	24	25	24	24
R^2	0.890	0.949	0.953	0.930	0.955	0.957
Adjusted R^2	0.875	0.941	0.940	0.921	0.948	0.945
Note:				*p<0.1; **p<0.05; ***p<0.01		

Note: Columns 1-4, 2-5, 3-6 correspond respectively to the equations (3.29), (3.29), (3.30).

Figure 3.F.18 – Forecast of the bias of technical change using our framework vs the true value (grey)



Note: The best specification for each of these sector is the one minimising the relative error (RMSE). The specification minimising forecast error on labour share is also the best fit on the direction of technical change. We indicate the specification for each sector: equation (3.30) for the agricultural sector, equation (3.28) for the paper sector, equation (3.30) for the financial sector, and equation (3.29) for the manufacturing sector.

Figure 3.F.19 – Forecast of labour share using our framework vs the true value (red) — with different length of the training versus testing set

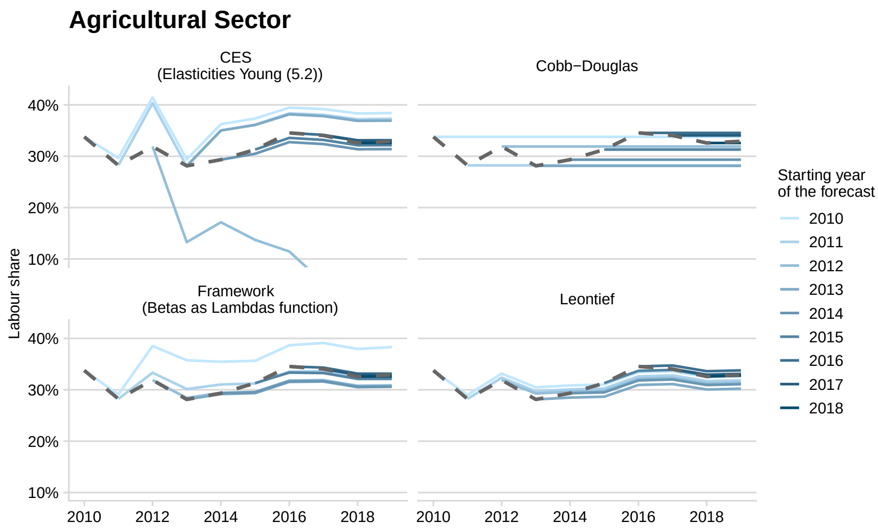


Figure 3.F.20 – Forecast of labour share using our framework vs the true value (red) — with different length of the training versus testing set

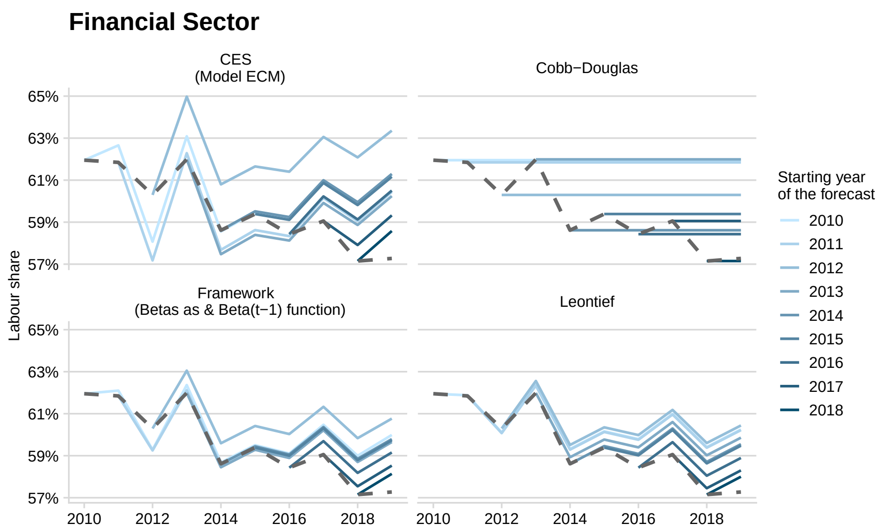


Figure 3.F.21 – Forecast of labour share using our framework vs the true value (red) — with different length of the training versus testing set

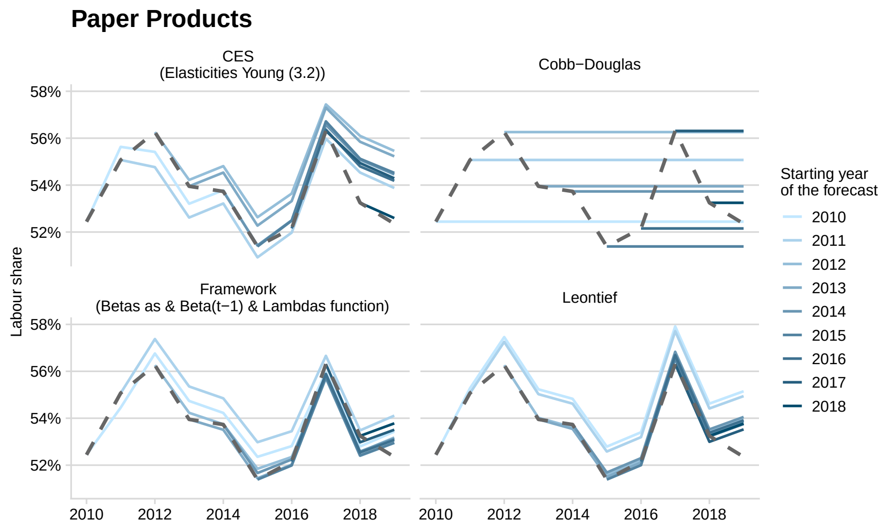
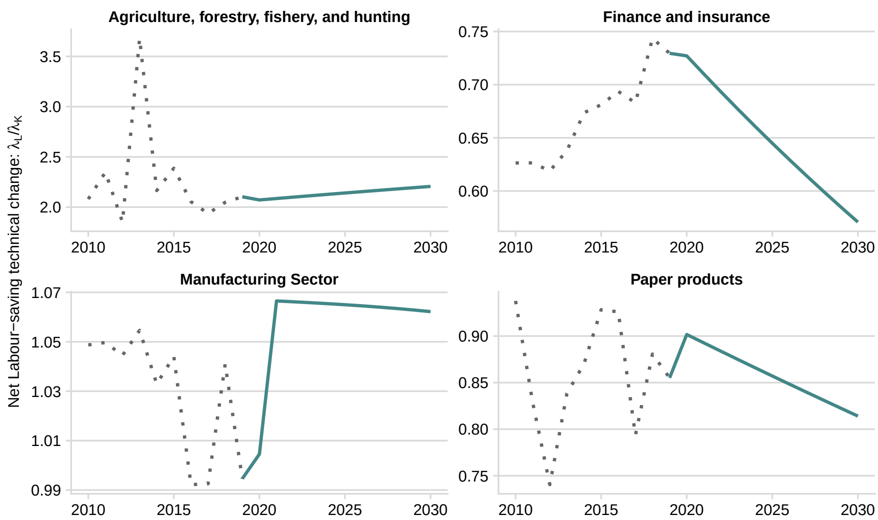
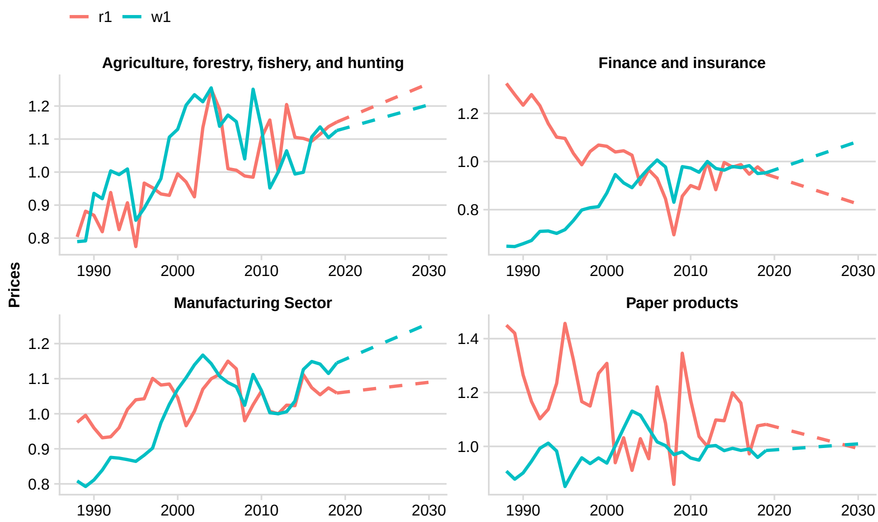


Figure 3.F.22 – Forecast of the bias of technical change up to 2030 for four industries



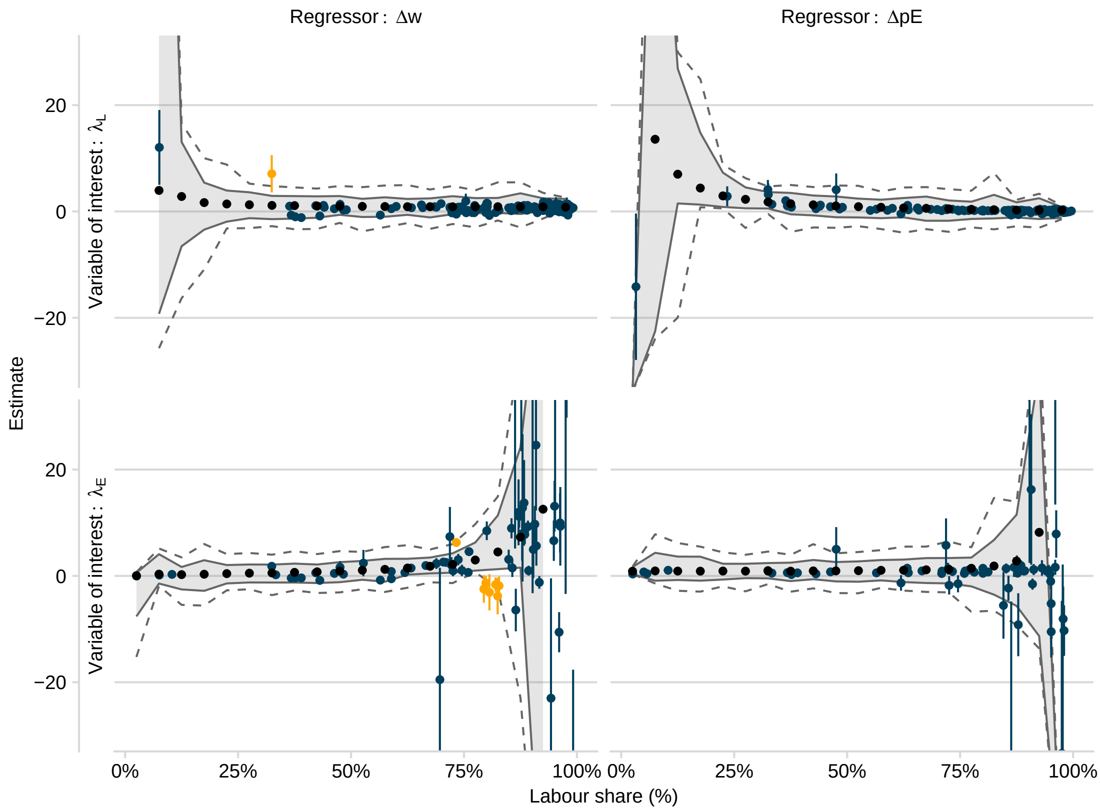
On retient la meilleure spécification sur la période 2013-2019 de notre framework.

Figure 3.F.23 – Forecast of the prices of factors up to 2030 for four industries



Proejction linéaire estimée sur la période 1987-2019.

Figure 3.G.24 – Estimation of the relationship between the intensity of technical change ($\lambda_{(L,E)}$) and price variation ($\Delta W, \Delta p_E$)



Note: The point estimates are plotted against the labour share. See figure 3.24. Data: KLEMS US (1986-2019), KLEMS EU+ v2008 (1970-2005)

CHAPTER 4

Economic and environmental performances of natural gas for heavy trucks: A case study on the French automotive industry supply chain

Joint work with Pascal da Costa (Université Paris-Saclay)

> Roulé de six heures à minuit à travers des montagnes couleur d'anthracite pour atteindre Zadihan : maigres eucalyptus, lune de comédie et, au centre d'un carrefour de sable, un gendarme qui n'en revenait pas de voir surgir à pareille heure et à ce bout du monde cette voiture sans lumière d'où dépassaient le manche d'une guitare et le col d'une bouteille, conduite par deux spectres qui paraissaient sortir de la saumure.
>
> Nicolas Bouvier, *L'usage du monde*

Abstract

Road transport is a major CO_2 emitter that can be reduced by using alternative fuels. This chapter offers a micro-simulation of the adoption of compressed natural gas in heavy-duty vehicles based on real French data on industrial flows in 2018 from the automotive manufacturer Renault. Our purpose is to assess the potential of natural gas as a transition fuel for the supply chain by determining the economic conditions under which natural gas is both economically and environmentally beneficial.

We consider two types of natural gas: bio-sourced and fossil. Both types of gas trucks prove cost-effective for long-distance flows within a short 5-year time period. However, fossil-fuel natural gas trucks emit from 3 up to 13% more CO_{2eq} than diesel trucks on the same trip, due to the extra kilometres required to reach refuelling stations (+6.21% of distance covered on average). Conversely, compared to diesel trucks, bio-sourced gas reduces the carbon footprint of transportation up to -76%. Thus, only bio-sourced gas proves to be favourable. We also investigate other types of externalities, such as air pollution and noise. We finally find that carbon taxes should be based on life-cycle emissions in order to boost wider adoption of biogas.

1 Introduction

Global energy consumption and greenhouse gas (GHG) emissions are now peaking at around 13.7Mtoe and 32GtCO_2 (IEA, 2018). The transport sector is regularly singled out as a major energy consumer, as it accounts for 29% of final energy consumption and 25% of global GHG emissions. Emissions from transport have risen by 71% since 1990, and the trend is likely to continue increasing in the coming years.

At the same time, the Paris Agreement set the goal of remaining below a 2°C rise in temperatures, and governments have set targets for each sector of their economies. The French transport sector is to reduce its carbon footprint by more than 6% between 2019 and 2023 (SNBC, 2018) while compensating for its insufficient efforts over the 2015–2018 period (Le Quéré, 2019). Heavy-duty vehicles (HDVs) are a strategic focus for reducing net transport-sector emissions in France as the small fleet is a big carbon emitter, and so the focus is on carriers to intensify their efforts. Indeed, HDVs emit as much as half of the private vehicles fleet with 60-times-fewer vehicles (CGDD, 2019); HDVs account for 6.3% of the national carbon footprint whereas private cars stand for 15.7%.

The trend in efforts to reduce road transport emissions has long been based on reducing fuel vehicle consumption (Yeh, 2007), but despite undeniable progress, attention is now moving towards alternative fuels such as natural gas for vehicles (NGV) (Bicer and Dincer, 2018; Sangeeta et al., 2014). NGV is now a mature and readily available option that has developed since the 1930s for private cars (Yeh, 2007). NGV is used by internal combustion vehicles that operate relatively close to diesel combustion vehicles, which means production and deployment only require incremental innovation (Wang-Helmreich and Lochner, 2012). Plant-based biodiesel is available as an option to reduce GHG emissions, but its environmental impacts are complex to assess, and still unknown (Hosseinzadeh-Bandbafha et al., 2018). Hybrid, hydrogen, or electric heavy trucks will not become widely available in the short term, and they are also widely criticised as environmentally unsustainable as they are dependent on manufactured batteries and the electricity power mix (Bicer and Dincer, 2018; Doucette and McCulloch, 2011).

The purpose of this paper is to investigate what political and economic conditions would be needed for natural gas trucks to succeed in reducing GHG emissions while ensuring their economic profitability. Our core contribution is that we study the penetration of this technology during the adoption and transition period and then look at designing appropriate policies to support environmental-friendly use of NGV. We find that NGV requires significant average detours (+6.21%) to reach refuelling stations, thus increasing the GHG emissions of compressed natural gas (CNG) over diesel. A well-to-wheel (WtW) carbon tax based on the life-cycle emissions of the gas proves to be the best tool to incentivise the use of bioCNG. In all the scenarios developed here, the fuel needs to blend in 30% of biosourced gas to reduce CO_{2eq} emissions by at least 6% to reach emissions reductions objectives.

The originality of this chapter is that it is based on spatial data for both flows and the current refuelling stations network, within the framework of the French supply chain of the automotive manufacturer Renault. This automotive industry has oligopolistic characteristics, but rivalry is fierce. Automotive firms have to operate under intense price competition, and the industry is notoriously tight-margined. Cost issues are therefore likely to play a critical role in the sector's decision to opt for a greener supply chain. Consumers' willingness to pay for a more sustainable supply chain is low, hence an increase in costs will not be reflected in selling prices (Lane and Potter, 2007). Any adoption of technologies to reduce carbon emissions is hence conditional on the economic profitability of the allied investment.

This chapter is a case-study of the two previous chapters, and it studies an innovation in the transport sector. The use of biogas trucks is carbon and energy-saving, which is why the switch is profitable for the firm.

The transition to natural gas from diesel is capital and labour-intensive. Gas trucks are more expensive per unit than diesel trucks, and to benefit from a refuelling station within the plant — which limits detours — the firm needs to massively and rapidly invest in a fleet of trucks. Gas trucks require more maintenance and force drivers to make detours to refuel, they reduce labour productivity and thus create jobs. On a broader scale, biogas production also allows jobs to be relocated in France, as the construction of the network of gas refuelling stations will require construction work.

The chapter is organised as follows. Section 2 outlines the state of the art in both economic and environmental benefits of NGV. Section 3 presents simulations of replacing diesel trucks by natural gas trucks on a company's real freight flows in France and details the assumptions, methodology and scenarios framework employed. Section 4 presents and analyses the results, we also discuss the levels of taxes and subsidies needed to ensure profitability. Section 5 concludes the work and draws the policy implications of this study.

2 Literature review

There are three main gaps in the current models of NGV trucks highlighted in this literature review. Our study is designed to address all three of these gaps.

First, we show that few studies focus on CNG trucks and even fewer assessing CNG for HDVs on long-distance trips in real-world conditions. However, other applications of CNG, such as refuse trucks or city buses, have been studied in various countries. Laboratory research and real-world studies have highlighted lower GHG emissions from CNG compared to liquified natural gas (LNG) (Khan et al., 2015; Meyer et al., 2011). Section 2.1 details these results and reviews additional articles in the literature, and concludes that the use of CNG for long-distance HDVs proves a promising avenue for research.

Second, both on-site studies (Schnetzler and Baouche, 2019) and numerical simulations (Lajevardi et al., 2018) conclude that fuel consumption, emissions and profitability are dependent on real-word conditions, i.e. factors such as road profile, detours to reach refuelling stations, engine efficiency, type of driving, etc. We call these factors 'hidden costs', as they do not appear in a theoretical framework. Section 2.2 details the relevant studies and their conclusions. We conclude that to assess the real performances of CNG and design appropriate support policies, we need to use real-world data and reveal some of these hidden costs. Here we explicitly model two hidden costs: real engine consumption, and lack of refuelling infrastructure leading to detours.

Third, section 2.3 reviews the impact of support policies on the investment decision-making process. Few studies have computed the effect of carbon taxes (Morrison et al., 2018) or subsidies (Heimer et al., 2017) on CNG truck purchases. The deployment of a larger NGV refuelling network appears to be the key condition for making CNG attractive at national level. To our knowledge, the quantitative impact of refuelling-network density on CNG investment decisions and profitability has never been investigated.

The rest of the chapter therefore addresses these three gaps by focusing on CNG HDV for long-distance applications and by explicitly accounting for detours and fuel consumption. Finally, we compute the impact of different support policies and the level of subsidy required to trigger investment.

2.1 Compressed and liquified natural gas for vehicles

NGV is the same natural gas used for domestic purposes. To increase its energy density (and thus the range of vehicles), natural gas can be either compressed at 200 bars (CNG) or liquified at -162°C (LNG). We do not consider hybrid configurations such as CNG-LNG trucks or LNG-diesel trucks. The objective would be to combine the greater range of LNG and the availability of CNG from the domestic networks, but the expenditure involved in building a dual-fuel truck makes HDVs purchase too costly (Gao et al., 2013).

Gas storage mode, i.e. liquified or compressed, is one of the key drivers of the uncertainty in emissions. Liquefaction is an energy-intensive process which, once completed, requires transport of the gas by purpose-adapted tanker trucks or by ship, and no longer through a pipeline network: these two stages are both local and global sources of pollution (Hagos and Ahlgren, 2018b; Khan et al., 2015).

There is no consensus on how CNG and LNG CO_2 emissions levels compare. However, methane leaks must be considered on top of CO_2 emissions as they could generate more environmental damage than diesel (Cooper and Balcombe, 2019; Camuzeaux et al., 2015; Cai et al., 2017). LNG emits three times as much methane as CNG, and so the CO_2 equivalent emission indicators (CO_{2eq}) argue for CNG against LNG (Ventura et al., 2017). Indeed, Meyer et al. (2011) find that for CO_2 emissions only, CNG is to be preferred over LNG (-8.3% and -4.2% CO_2 emissions, respectively, versus diesel), and when considering all GHG (CO_{2eq}), LNG emits even more than diesel (+0.6%) while CNG loses environmental benefit (-3%).

As the on-road stage is very GHG-intensive, some studies have focused exclusively on this phase without integrating the upstream emissions, whereas the liquefaction and road transportation of LNG is very energy-intensive and increases the upstream emissions of LNG compared to CNG (Ademe, 2014). Most empirical HDV studies have focused on LNG, as it offers greater range thanks to its higher energy density (Meier et al., 2013).

Despite uncertainty regarding GHG emissions, CNG appears to have lower GHG emissions on a WtW life-cycle basis than Diesel and LNG. There is consensus that using CNG brings local-level gains in air pollutants such as NOx and fine particles, or even noise, at least for the original equipment manufacturers (Reynolds et al., 2011; Yeh, 2007). However, hydrocarbon and carbonyl (in particular formaldehyde HCHO) emissions are higher for CNG than diesel (Anderson, 2015). CNG buses emit more carbon monoxide (CO) than diesel buses (Hesterberg et al., 2008), while CO emissions are not found significantly different for trucks (Anderson, 2015). Fitting CNG trucks with an exhaust catalyst—oxidation catalysts or three-way catalyst—can significantly reduce HCHO, NOX and CO emissions (Thiruvengadam et al., 2015; Yoon et al., 2014), and unburnt methane emissions (Khan et al., 2015). Bicer and Dincer (2018) find that CNG has a low toxicity index at a level close to 10 times below electric vehicles and only bettered by hydrogen vehicles.

Local pollution is now a major environmental issue in large cities (Chan and Yao, 2008). NGV is seen as part of the solution in the city of Delhi (India), where all public transport has been running exclusively on CNG since 2001 (Pal et al., 2009). CNG is a common solution for urban applications such as refuse trucks (Shahraeeni et al., 2015; López et al., 2009) or bus networks, with up to 34% less GHG emissions compared to diesel in the US and Brazil (Galbieri et al., 2018; Shahraeeni et al., 2015; Chandler et al., 2006). However, there is still no large-scale empirical study focused on HDV running on CNG.

In this chapter, we focus on CNG as an alternative fuel for HDVs, which unlike LNG is already biosourced and is produced by the methanisation of waste or biomass, (NGVA, 2017). The International Energy Agency (IEA, 2010) warns that while natural gas can play a role in reducing CO_2 emissions, in the long term the transition to clean sources of natural gas still requires ambitious support policy.

2.2 Empirical conditions and determinants of ecofriendliness and profitability for NGV

Measuring the environmental performance of a vehicle is a notoriously tricky task as the results can be affected by a variety of factors. Empirical studies and full-scale tests are essential to resolve emissions uncertainty. Discrepancies in CO_2 and GHG emissions can be partly explained by a difference between the theoretical and actual efficiency of fuels and engines (Shahraeeni et al., 2015).

Both the profitability and emissions results of any model are extremely sensitive to the modelling choices made to detail certain parameters and the variables considered. For instance, travel speed and the particular road chosen for the trip appear to influence transport ecofriendliness (Kirschstein and Meisel, 2015), and it is also important to consider truck type, load weight, road profile (flat, hilly, mountainous), and road type (motorway, urban road, etc.) as part of the emission factors (Hausberger et al., 2009). Taken together, the interplay of these factors is such that they influence the comparative environmental performances of two competing technologies. For instance, real consumption is 33.7% lower for diesel trucks than CNG trucks on urban high-speed roads (22.2kg CNG/100km *vs* 16.6kg diesel/100km) but only 3.8% lower in dense urban areas (36.1kg CNG/100km *vs* 34.8kg diesel/100km) (Schnetzler and Baouche, 2019). Neglecting road grade can lead to underestimate CO_2 emissions by as much as 24% for Lajevardi et al. (2018), compared to 18% for Quiros et al. (2016). Thus, on-road efficiency is part of the hidden costs and emissions factors that play a huge part in the investment decision.

It is crucial for any new technology to be profitable independently its emission reduction potential, since profitability critically shapes the technology adoption decisions taken by private firms, especially in cost-pressured sectors such as car manufacturing. For CNG vehicles, the economic impact outweighs the GHG reduction objectives (Sharma and Strezov, 2017). Over the same distance travelled, the difference in price between gas and diesel will allow more profit in the case of large volume consumption, as in the case of heavy-duty vehicles (HDVs), than in the case of light-duty vehicles that consume less (Cai et al., 2017). We show in the rest of the study that other parameters affect the profitability of HDVs, such as the lack of stations and the detours needed.

Based on payback period alone, non-hybrid natural gas vehicles appear to be the most economical option (Krupnick, 2010). Given a sufficiently long travelled distance, LNG trucks could even be profitable within one year (Hao et al., 2016).

Lack of refuelling infrastructure cause drivers to divert their route to reach a gas station. In the US, natural gas vehicle owners declare an average detour of +46.7% from their regular route, whereas regular car owners only declare a detour accounting for 19.1% of their trips. CNG car owners estimate an added 29%–64% travel time (Kuby et al., 2013). In Los Angeles (USA), this additional time is not only inconvenient but costs from \$22 up to \$39 on refuelling days including fuel cost and time lost in congestion (Kang and Recker, 2014). This extra detour influences purchase decision, but its effect decreases with the development of alternative fuels and more refuelling stations (Morrison et al., 2018). However, most papers do not take detours into account in their cost breakdown. Here we consider the extra cost of detours to challenge the scholarship's conclusions on the profitability and emissions of CNG trucks. We express each flow's real distance including refuelling deviation, which is more precise than interviews (Kuby et al., 2013).

Next, the empirical CNG research appears to have under-addressed the influence of oil price trends. Oil prices will likely increase as oil reserves become scarcer, but geopolitical tensions in oil-producing regions can also cause significant fluctuations in the price of oil. Most studies model the cost breakdown of CNG investment as an extra cost on the purchase and a gap in fuel prices multiplied by a given annual distance (Mouette et al., 2019; Hagos and Ahlgren, 2018b; Hao et al., 2016; Krupnick, 2010). Galbieri et al. (2018) studied projected fuel prices by 2035 in Brazil but ignored the tricky transition period, which is key to technology entrenchment, and hence the most likely outcome would be an abandon of natural gas projects, as was the case in Germany (von Rosenstiel et al., 2015), Canada (Flynn, 2002) and New Zealand (Yeh, 2007).

To our knowledge, no study has considered the impact of fuel price trajectories in NGV market growth. Since the breakeven use/duration of a fleet is unlikely to be less than a year, it is necessary to factor fuel and gas price changes over the years as a key input to the investment decision. The contribution of this study is to reveal the hidden cost of implementing NGV based on evolving cost factors such as fuel or the growing refuelling network, as well as the detours and maintenance needed in real-world-flow practice.

2.3 Supporting natural gas: policies and barriers

Governments are pushing for rapid development of the NGV market, and incentives have a crucial role to play in helping to develop a steady market for natural gas as an alternative fuel (Flynn, 2002). The 2017 French Mobility conference set the objective of 30% of the national trucks, buses and coaches fleet run on gas by 2030. Policies praise natural gas due to its high energy-to-carbon ratio, which offers great potential to reduce GHG emissions (Khan et al., 2015; Rose et al., 2013). However, no scientific consensus has been reached yet on the net environmental benefits of natural gas for transportation nor its profitability compared to diesel (Hao et al., 2016; Krupnick, 2010). And even if the environmental goal could be achieved, the decisive factor remains economic (Sharma and Strezov, 2017).

The challenge for expanding the use of an alternative fuel such as natural gas is to make it both economically and ecologically attractive to diverse users and producers. Hence government policy in favour of NGV uptake needs to establish the natural gas ecosystem (Flynn, 2002; Yeh, 2007). A clear and steady path of government support should then offset the uncertainty of fuel prices.

By incentivising the production of natural gas, governments make it viable to develop the refuelling stations network (Engerer and Horn, 2010). A carbon tax also increases the profitability of refuelling stations as can be used to make a larger number of NGV segments competitive comparatively to conventional fuels (Morrison et al., 2018).

The bottlenecks to development of gas-powered vehicles include the small network of gas stations, the technical standards that vehicle-makers need to meet, the limited choice in available offers, and the financing and profitability conditions of the investment (Jaffe et al., 2016).

Note that even if effective, the effects of policies may be long to emerge, due to the long delays between measured indicators (sales and infrastructure expansion) and current policies (Janssen et al., 2006). This long-term approach makes it unclear whether subsidies will have a significative influence on the market (Heimer et al., 2017).

3 Methodology: cost breakdown applied to real-world-flow data

3.1 Scope and real-world-flow data

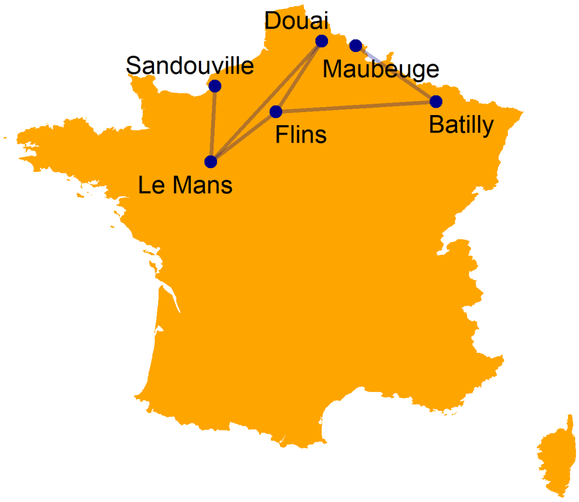
Renault's Traffic database records all Renault-Nissan flows in Europe in the period 2015–2017, detailing flow characteristics including volume and distance. We use cost assumptions to determine the microeconomic profitability of each flow using CNG instead of diesel. The major asset of this database is its level of disaggregation which allows us to go beyond an average mileage. We reproduce the effective route of each truck, which serves for example to identify the deviation from the shortest path to reach a natural gas station.

We focus on intra-France routes to deal with the French legislation and refuelling network. We choose to focus on CNG rather than LNG due to ecological reasons discussed in section 2.1 and the already large number of CNG stations. From the 240,000 transport units delivered on a France-to-France route in 2017 (2598 axis), we only consider 42 flows corresponding to 39,000 transport units between major plants in Renault's chain of production (Fig. 4.1). Pre-selection was composed of steady flows that can sustain daily back-and-forth (round trip) activity. When number of flows from B to A is inferior (due to empty packaging optimisation) than the A to B volume, we retain the smallest number. We consider only flows that could feasibly be handled in gas using the current CNG refuelling stations map, i.e. the distance between to refuelling points had to be less than 340 km, including a safety margin drawn from Renault expertise (based on manufacturer claims of more than 500 km range for CNG HDV). This pre-selection offers carriers an insurance that their investment in a CNG truck will generate enough activity to be profitable without further need to look for other customers than Renault.

The profitability of investing in CNG is assessed by the net present value (NPV) of the investment I in year 2018 (base year), plus the discounted gains (R_i), with the years i from 2018 to 2022, before the truck is sold back at 10% of its value (in accordance with generally accepted market conditions):

$$NPV = -I + \sum_{i=2018}^{2022} \frac{R_i}{(1+\delta)^{i-2017}} \tag{4.1}$$

Figure 4.1 – Flows eligible for conversion to natural gas related to core Renault plants in France



Discounting factor was set at $\delta = 20\%$ to account for the 5-years depreciation of a HDV. A profitable flow, with a strictly positive NPV over 5 years, is automatically considered as switching from diesel to CNG.

3.2 Cost assumptions

Costs can be separated between fixed costs (independent of distance travelled) and variable costs (that depend primarily on the truck's activity). Fixed costs are further subdivided into material investment and human resources. Variable costs include fuel and maintenance.[1] Details can be found in Table 4.1 (data on other steps are available as supplementary material).

Most of the cost assumptions come from the French National road committee (CNR, 2018). The extra investment in a CNG truck is profitable compared to an equivalent diesel truck as it is offset by a reduction in fuel cost. As price is widely available data common to most studies, the real fuel consumption of trucks is the key parameter to assess the economic value of switching to CNG (Schnetzler and Baouche,

[1] Let us point out that we have not explicitly taken into account the difference between CNG and Diesel trucks in terms of the cost of exhaust clean-up systems to reduce pollutant emissions. Indeed, the three-way catalyst technology for CNG HDV exhausts reduces NOX emissions at a lower price than diesel technology and with less complexity and thus greater durability (Thiruvengadam et al., 2018). This new cost item is in line with the greater profitability of CNG compared to diesel, and supports our results.

Table 4.1 – Comparative cost breakdown of diesel, CNG and bioCNG

	Material investment			
	Diesel	CNG	mixCNG	bioCNG
Commitment duration	5 years	5 years	5 years	5 years
Biogas percentage	0%	0%	30%	100%
Investment	€85153	€109000	€109000	€109000
Truck price after negotiation	€85153	€109000	€109000	€109000
License and registration	€850	€5	€5	€5
Truck buyback price after 5Y	€20000	€10900	€10900	€10900
Financing rate	1%	1%	1%	1%
Monthly cost of material	€1145	€1 686	€1686	€1686
Total cost of material (5Y)	€68694	€101164	€101164	€101164
	Human resources			
Monthly hours	220 h	220 h	220 h	220 h
Manpower (full-time equivalent)	1.00 FTE	1.07 FTE	1.07 FTE	1.07 FTE
Hourly wages	€18.32	€18.32	€18.32	€18.32
Total monthly cost	€4029/mo.	€4311/mo.	€4311/mo.	€4311/mo.
Total 5Y cost	€241766.12	€258689.75	€258689.75	€258689.75
	Variable cost			
Average fuel price over 5Y	€1.2703/L	€0.8631/kg	€0.8931/kg	€0.9631/kg
Consumption	29.7L/100km	27.0kg/100km	27.0kg/100km	27.0kg/100km
Average fuel price/km	€0.340/km	€0.233/km	€0.241/km	€0.260/km
Maintenance	€0.074/km	€0.089/km	€0.089/km	€0.089/km
Tyres	€0.039/km	€0.039/km	€0.039/km	€0.039/km
€/km average	€0.490/km	€0.361/km	€0.369/km	€0.388/km

2019). The difference in fuel consumption (kg/100km) is 8% in favour of CNG on primary roads (most often used by trucks). According to Renault experience and carrier-reported consumption figures, we assume a fuel consumption of 29.7 L/100km (or 25.1 kg diesel/100km) for diesel HDV and 27kg/100km for CNG HDV.

This study explicitly models two hidden costs: detours and real consumption. Detours are a hidden cost because they are not an explicit line on the cost breakdown, but we model them explicitly by computing the extra variable cost due to additional distances travelled to reach refuelling points. We also consider that real fuel consumption is also a hidden cost in that it is partly due to human behaviour and environmental conditions. We address this by using real consumption based on Renault field expertise, instead of the theoretical fuel consumption of the trucks.

3.3 Scenarios structure: integrating uncertainties

Precise flow data allows us to anticipate the truck's journey for each flow and plan out the refuelling stations where each truck will have to stop, according to the current stations map, and the real range of CNG trucks. For each flow, we possess data on the actual distance driven in diesel and natural gas, including detours made to refuel with gas at the beginning, middle and end of the route.

Firm's commitment to CNG. The increase in refuelling network density would limit the costly detours for carriers. We split the firm's commitment into three steps. A first step (Step 1) is a low commitment from the company: less than 10 flows are converted to natural gas. We can consider this step as an introductory trial that has to be conclusive for the company to commit to a massive en-bloc purchase. The second step (Step 2) is a massive commitment to a cleaner technology, allowing a discount on quantities purchased. The last step (Step 3) requires a massive supply chain-wide conversion and significant investment to purchase a new fleet. If there are enough flows serving a plant, it is possible to install a CNG station directly next to the plant. No investment is needed from the company, given that the daily truck traffic is high enough to ensure the profitability of a gas operator installing a station near a company's plant. Note that a scale effect is at work, as the logistics mobilises an entire fleet of trucks. Carriers therefore usually make bulk purchases to secure a discount price. We estimate based on Renault expertise that the bargaining power of carriers against truck manufacturers is 5% for steps 2 and 3.

This three-step procedure allows the scenario to remain profitable for refuelling station operators. As the first two steps require no additional stations, we based our calculations on existing stations in France (as of November 2018). The French NGV advocacy platform (AFGNV) issues periodic updates on newly-created stations.

Diesel price uncertainties. As there is uncertainty over changes in diesel prices, we study two price evolution scenarios: a 'Central' scenario which is the more likely according to Renault's in-house research, and a 'Black' scenario where the price per barrel soars. We anticipate that the price of natural gas for vehicles will be more stable by 2022, and so we consider only one scenario. Prices are given in the supplementary material.

CNG Composition. Nonetheless, the gas price scenario may vary depending on whether it is fossil or bio-based or a mix of the two. The chapter refers to these different fuels as CNG, bioCNG, and mixCNG.[2]

3.4 Greenhouse gas emissions

GHG emissions for fuel are expressed as a quantity of carbon released for a certain quantity of fuel (kg or L). Tank-to-wheel (TtW) emissions are the emissions due to combustion of one litre of diesel or one kilogram of gas. WtW analysis includes the upstream emissions related to extraction, refining and transport of the fuel (Well-to-Wheel). Table 4.3 summarises the emissions corresponding to both WtW and TtW per

[2]It is possible to imagine a ramp-up scenario, starting with Step 1 as a test phase, then through Step 2 until the construction of stations in Step 3. A company may gradually increase the share of biogas in its energy mix to compensate for the increase in relative price of diesel compared to CNG. Only typical cases are presented here, so both the ecological and economic performance results of such ramp-up scenarios would be an approximately linear combination of the results presented.

Table 4.2 – Scenarios and assumptions

Diesel price evolution	
Central Scenario	Diesel from €1.054/L (2017) to €1.426/L (2022)
Black diesel scenario	Diesel from €1.230/L (2017) to €1.723/L (2022)
(Carbon Tax)	Carbon tax from €30.5/tonCO_2 (2017) to €86.2/tonCO_2 (2022)
Firm's commitment	
Step 1	$\leq$ 10 flows converted to NGV
Step 2	All profitable flows converted to CNG at 5% purchase discount
Step 3	Step 2 & refuelling station near to the plants
CNG composition	
CNG	Fossil Natural Gas
mixCNG	30% biosourced gas & 70% fossil natural gas
bioCNG	100% biosourced natural gas

kg of fuel and per km. The TtW CNG emission coefficient (regardless of source) is 2.78 kgCO_2/kg gas, while the respective coefficients of CNG and bioCNG are 3.48 and 0.82 kgCO_2/kg gas. Indeed, methanisation is considered as 'capture' of CO_2 (which makes the WtW coefficient negative), which makes it doubly attractive. The source used for the emissions coefficient is the French Environment Agency (ADEME[3]) 'Base Carbone', version 11 (Ademe, 2014).

3.5 Other externalities

Negative *externalities* are the collateral damage of an economic activity whose costs are not directly paid through production or consumption by the economic agents who cause them—the costs are instead borne uniformly by society (including the environment). The externalities of transportation can be collapsed into seven categories: congestion, accidents, noise, pollution, climate change, infrastructures, and others (Delft, 2016a,b, 2015, 2011; RICARDO, 2014; Vickrey, 1963)

CNG reduces the externalities of diesel on three fronts: i) GHG emissions, ii) air pollution, iii) noise levels. These three externalities can be measured relatively accurately and monetised in order to balance them against the cost of the policies to reduce them.

CNG can reduce pollutants by nearly 80% (which is the official figure given by the manufacturers for NOx and PM (NaturalGas.org, 2019) compared to Euro VI-standard diesel[4], which is far less than the 88-fold coefficient given by Pietikäinen et al. (2009)

[3]Agence de Maitrise de l'Energie et de l'Environnement

[4]Knowing that the Euro IV standard already marks a 92% decrease in acceptable NOx limits compared to the EURO III standard: https://www.ecologique-solidaire.gouv.fr/normes-euros-demissions-polluants-vehicules-lourds-vehicules-propres. Euro III standard is 7 gNOx/kWh against 0.4 gNOx/kWh for Euro VI.

Table 4.3 – Emissions coefficients for diesel, CNG, bioCNG and mixCNG

	Diesel	**CNG**	**mixCNG** (30% biosourced)	**bioCNG**
WtT ($kgCO_{2eq}/kg$)	0.78	0.7	-0.10	-1.96
TtW ($kgCO_{2eq}/kg$)	2.97	2.78	2.78	2.78
WtW ($kgCO_{2eq}/kg$)	**3.75**	**3.48**	**2.68**	**0.82**
Consumption	29.7 L/100km 25.1 kg/100km	27.0 kg/100km 27.0 kg/100km	27.0 kg/100km 27.0 kg/100km	27.0 kg/100km 27.0 kg/100km
WtT ($kgCO_{2eq}/km$)	0.196	0.189	-0.026	-0.529
TtW ($kgCO_{2eq}/km$)	0.745	0.751	0.751	0.751
WtW ($kgCO_{2eq}/km$)	**0.941**	**0.940**	**0.724**	**0.221**
% WtW *vs* Diesel	**0%**	**-0.20%**	**-23.09%**	**-76.48%**

Reading: At equal mileage, CNG emits 0.2% less than diesel. CNG has higher on-road emissions (TtW) but 4% lower sourcing emissions (WtT – Well-to-Tank). The WtT step is negative for bioCNG, strongly reducing its WtW carbon footprint.

and reasonable compared to the literature (Lyford-Pike, 2003). Hagos and Ahlgren (2018a) claims "almost zero particulate matter (PM) emissions, 87 to 90% reduced NOx emissions, and 67 to 76% reduced hydrocarbon emissions at comparable fuel economy". There is also a consensus that natural gas vehicles are 50% quieter than diesel-powered vehicles (Hagos and Ahlgren, 2018a; Maji et al., 2008).

GHG reductions are very much related to the composition and source of the gas in question, which is not the case for noise or local pollution where only combustion matters.

There is a plethora of methods for assessing damage caused by GHGs, air pollutants and noise. In this study, we follow the methodology and figures given in (Delft, 2011), which provides a monetary estimate of externalities expressed in tonne-kilometres[5] for diesel trucks depending on type of road and age of the vehicles. The noise and emissions reductions translate into an equivalent reduction in externalities per kilometre.

[5] A tonne-kilometre (tkm) corresponds to the displacement of a ton of goods over one kilometre. The average load of a heavy vehicle is 10T, so a truck travelling 100 kilometres is considered to weigh 1000 tkm in the calculated externalities.

4 Results

4.1 Scenarios analysis: Biogas is the key to emissions reduction

The main assumptions are subdivided into several scenarios: the company's level of commitment ranges from step 1 to step 3, and fuel prices can follow a steady 'Central' scenario or a 'Black diesel' scenario in which the barrel price soars. Source of the natural gas considered can be of fossil origin or biosourced at 30% (mixCNG) or 100% (bioCNG). For each scenario and their particular assumptions, we select the flows allowing a net benefit compared to diesel (benefit is the reduced cost of fuel net of the extra investment cost of the CNG truck).

Figure 4.2 details the number of trucks for which CNG enables a net benefit compared to diesel, in real-world conditions. Cost savings and GHG reductions are reported in the lower matrix. Note that the percentage reductions in cost and emissions only encompasses CNG-converted flows. The company could convert 31 trucks to CNG with a medium level of commitment (Step 2) in the Central scenario, and could then save 1.7% of total operational cost on its routes' compared to the same 31 trucks running on diesel.

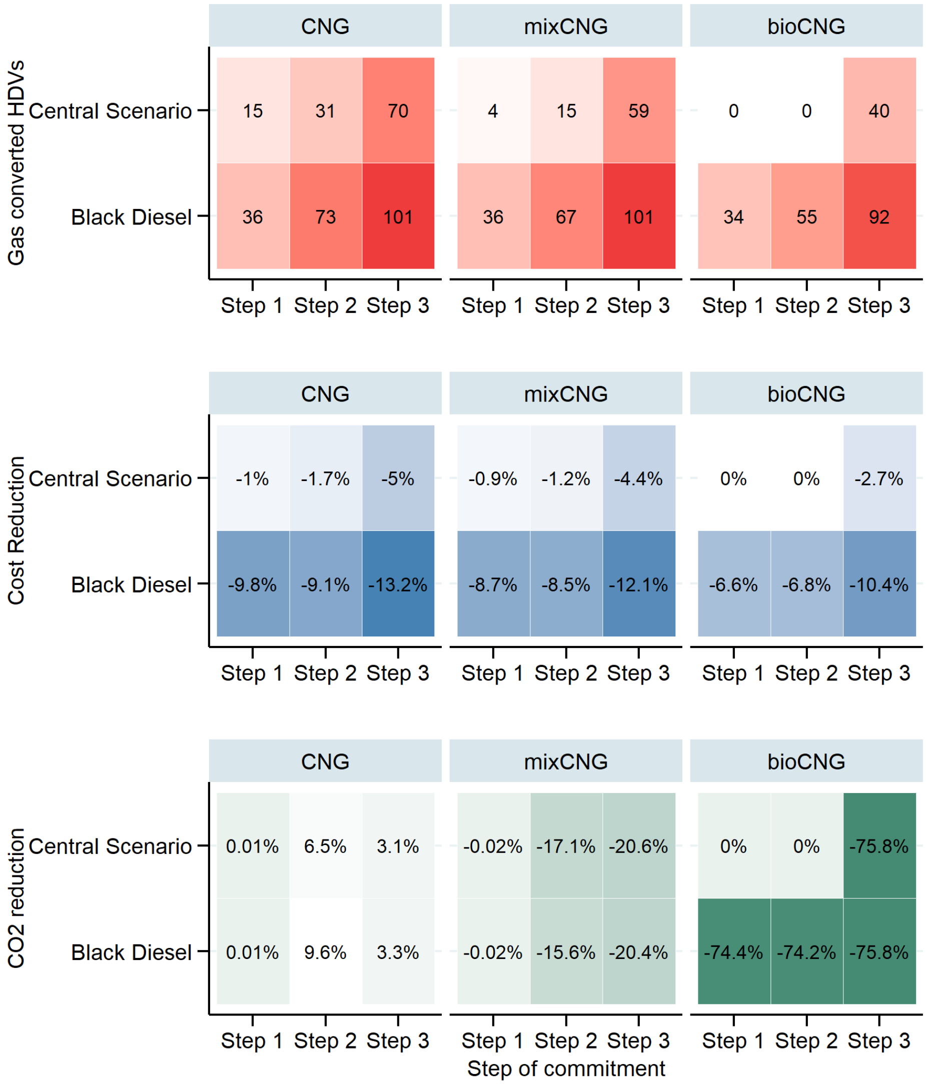
The Central scenario reaches profitability for at least 9% of the trucks converted to CNG and up to 42% with a higher commitment (step 3). As biogas is more expensive, it becomes barely profitable since the firm needs to make a high commitment (step 3) to make 40 trucks profitable in CNG compared to diesel. In contrast, the Black diesel scenario allows a trial phase with bioCNG where only the 10 best flows, corresponding to 34 HDVs, are converted to CNG, thus cutting costs by 6.6%. Indeed, with increasing commitment from the company, the percentage cost reduction increases while detours to reach refuelling stations decrease and investment is reduced as the carrier gains bargaining power. The most favourable situation is the scenario that widens the gap between gas and diesel prices at minimum cost (Black diesel x Step 3). The company could convert 32 out of the 42 pre-selected flows to bioCNG (>75%) or convert a maximum of 101 HDVs to CNG.

The first conclusion is that the profitability of CNG trucks in real flows depends on the global price of oil. Unsurprisingly, as biosourced gas is more expensive, the number of profitable flows is lower for bioCNG than for CNG and mixCNG, and the expected cost savings are also smaller.

However, the environmental benefits of NGV could become negative, as CNG may emit more GHG gases over a trip than diesel. No CNG scenario is able to cut emissions compared to diesel: the rise in CNG emissions ranges from 3.1% to 9.6%. In contrast, a 100% biogas scenario is able to cut around 75% of GHG emissions, including CO_2 and methane (CO_{2eq}).

Real flow conditions erode the environmental benefits of natural gas beyond the figures cited in section 2. Long-distance flows are the most profitable, as the fuel-price gap between gas and diesel offsets the extra investment cost of CNG trucks. As NGV

Figure 4.2 – Cost and emissions reductions for each scenario



Reading: In the Central scenario, in Step 2, adopting CNG will reduce on-road cost of CNG-converted routes by 1.7% whereas emissions increase by 6.55%.

trucks have limited range, long flows become characterised by numerous stops to refuel and detours to reach CNG stations. These extra distances increase both the price and the emissions of trips.

These results are typical of long interurban trips and are not therefore comparable to urban fleets (e.g. -34% in CO_2 emissions for a refuse truck fleet in Shahraeeni et al. (2015) or -12% in López et al. (2009)) where refuelling is not a problem, especially without considering the adoption period of the technology.

Figure 4.3 – Cost and CO_2 savings as a function of biogas share in the mixCNG scenario

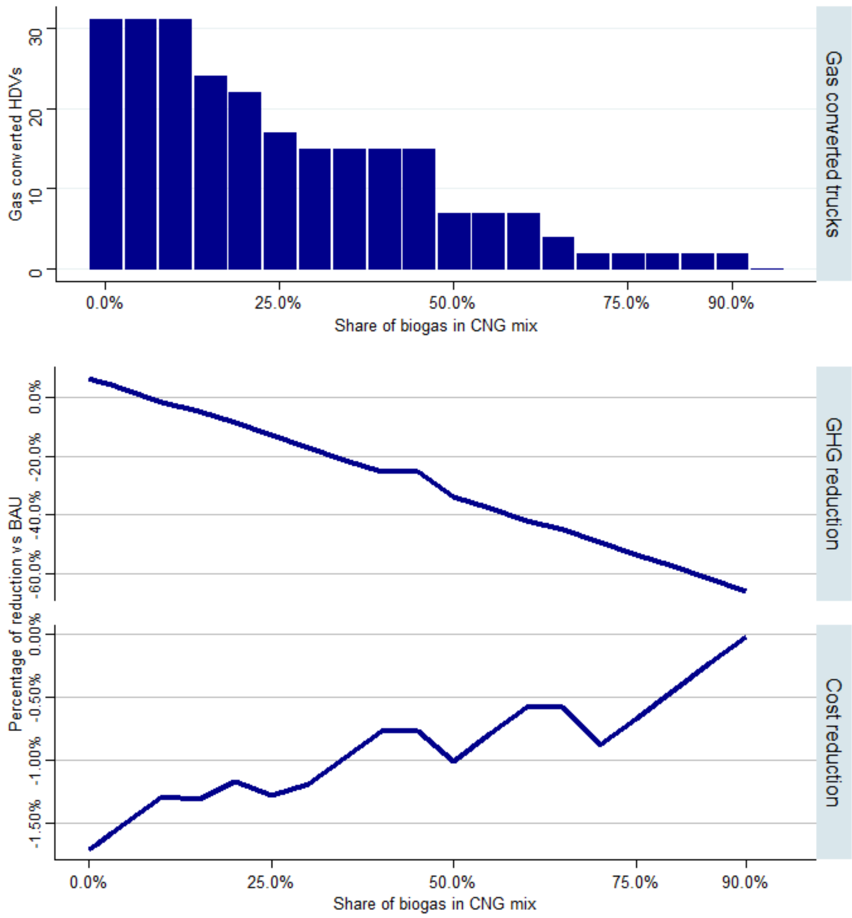


Figure 4.3 charts the trade-off between share of biogas and efficiency of conversion to CNG in terms of trucks on the roads, costs and emissions reduction in the particular case of Step 2 in the Central scenario.[6] Increasing biogas share in the fuel mix increases emissions reductions but decreases cost savings until diesel cost is reached. With 8.04% of biogas, the experiment reaches carbon neutrality compared to diesel within the same scope-frame as CNG (31 trucks, over 10 flows), whereas 90% biogas lead to more than 60% reduction in GHG emissions for bioCNG trucks compared to diesel.

The French Government's 2009 Carbon budget sets the transportation sector an objective of cutting GHG emissions by 6% (Quinet et al., 2009). A 21.3% share of biogas would allow the mixCNG flows to reach this objective for all scenarios studied

[6]NB: For both emissions and costs, the perimeter is variable and expressed as a percentage reduction only for routes that have switched from diesel to CNG (bio-sourced, mixed or fossil), which is why we see peaks in Figure 4.3 with thresholds where we lose routes that were just-about profitable to keep only the most profitable (i.e. a higher percentage gain).

here. For the rest of this study, we consider a mixCNG scenario with a 30% biogas share to ensure a larger CO_2 decrease to offset the remaining diesel flows. A larger share of biogas raises the price of the fuel while reducing its economic attractivity.

The French Multiannual Energy Programme (PPE) aims to produce 14 TWh of biogas domestically in 2023 and 32 TWh in 2028. The same source states a consumption of 192 TWh by road freight transport in 2016. The use of bioCNG could therefore only concern a fraction of the HGVs on domestic roads. The second conclusion is that CNG raises emissions in the real-scale situation compared to diesel due to the low density of the refuelling network, and biogas production capacity will be unable to sustain the entire market, making it difficult for natural gas to play the role of bridge fuel to enable the whole transportation sector to make its energy transition.

4.2 Key parameters and sensitivity analysis

One of the key parameters in our modelling of gas truck penetration is the detour imposed by the low density of the refuelling station network. This detour, which depends on the company's commitment to natural gas, averages between 3.82% and 7.41% for all flows considered (see Table 4.4). Indeed, Step 3 means a substantial commitment by the company of at least 40 trucks in bioCNG and 101 in CNG, which would be enough to make it profitable for a filling station to locate next to the plant, thereby reducing the detours need to refuel the trucks. Bigger detours lead to a smaller gap between diesel and CNG emissions. In the case of CNG, the detour more than offsets the emissions gains. The level of detail of our dataset allow us to define which routes are profitable for the company and which refuelling stations each truck stops at. Note that the cost of the additional labour required to drive these extra kilometres is not expressed on a flow-by-flow basis but as a 7% increase in full-time equivalents for Steps 1 and 2 and a 3% increase for Step 3. Not accounting for detours leads to overestimating the potential of natural gas, since all scenarios advise converting at least 29 HDVs into biogas.[7]

Clearly, it is the detours that kill the environmental performance of natural gas for vehicles, since all scenarios announce a CNG emissions reduction of 0.2%, which is close to the 0.6% calculated by Meyer et al. (2011) instead of a rise of 3.1 to 9.6%. If we neglect the position of the refuelling stations, we favour long trips, which is why the cost reduction reaches 9% by CNG for the Central scenario but is only 1% with the detours. Without the detours, our gains over 5 years are at best 18.8% compared to the Diesel scenario, i.e. more than 5 years to achieve payback. However, these estimates are based on price gaps of more than €1.50 whereas we consider gaps that are narrower at the beginning but at least as big at the end. This is why even without detours, our economic results are much less optimistic than Krupnick (2010) who asserted a payback in less than 2 years.

[7] For control purposes, we performed the calculations reported in Supplementary material without taking detours into account, thus neglecting both the additional distance covered and overtime hours required.

Detours are a hidden cost that dramatically changes the attractivity of NGV. Detours, extra maintenance costs, and a less optimistic gas consumption with a more detailed cost breakdown (see Supplementary material) explain the different conclusions of this study compared to Hao et al. (2016) or Krupnick (2010).

Table 4.4 – Detours in CNG *vs* diesel trips

CNG	Central Scenario	Black diesel scenario
Step 1	7.98%	7.70%
	(31.3 km)	(27.4 km)
Step 2	7.41%	10.14%
	(26.3 km)	(31.8 km)
Step 3	3.82%	4.01%
	(11.6 km)	(9.6 km)

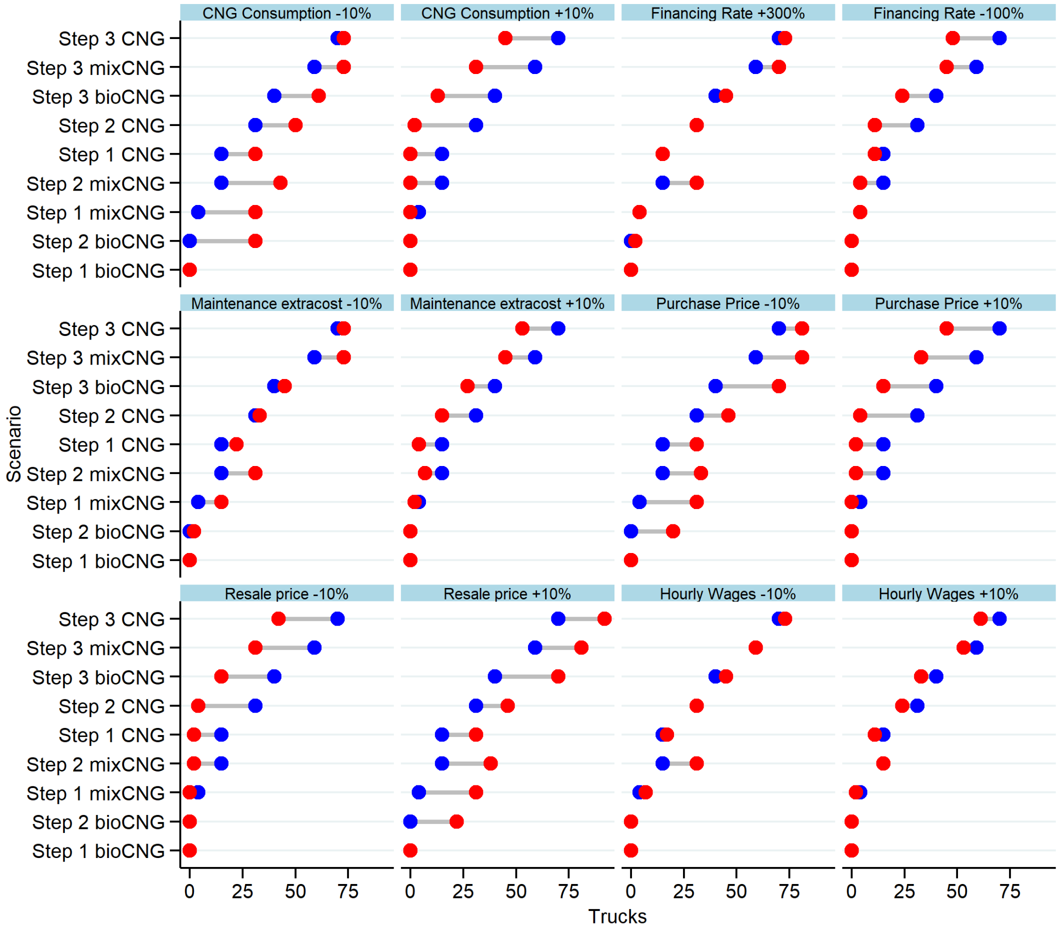
Conversely, neglecting the evolution of relative fuel prices leads to underestimating the attractiveness of CNG. Even with a diesel/gas price differential set at the 2018 level for the 5-year study period, natural gas for vehicles remains attractive for carriers and loaders. The switch to CNG would reduce operating costs for 5 out of 42 of them. The change would concern 9% of the trucks (15 trucks a day). These 5 flows would generate a €56k net present value (NPV) out of the switch to CNG trucks from 2018 to 2022 which represents 1.00% of the current operating cost for those routes using Diesel trucks (€5.7M over 5 years).

A fixed gap between natural gas and diesel is a very conservative assumption that does not contradict the economic attractivity of natural gas as HDV fuel. Carrier adoption of CNG technology is therefore possible as of now, and our simulation is robust on this parameter. Indeed, the relative price gap between diesel and CNG will only increase during the period (2018—2022). Increasing the carbon component in the fuel taxes will affect diesel more severely than gas. Meanwhile, it is likely—but not certain—that market fluctuations will increase oil prices. The second conclusion of this first simulation is therefore that neglecting the evolution of relative fuel prices leads to underestimate the attractiveness of CNG.

We selected this study's parameters based on input from the French National Roads Council (CNR, 2018), Equilibre report (Equilibre, 2018), the French Environmental Agency 'Base Carbone' database (Ademe, 2014), and supply chain experts at Renault. We tested the influence of a 10% error margin on uncertain parameters (CNG consumption per 100 kilometres, Financing rate, Purchase price, extra cost of maintenance, resale price, and hourly wages) on the number of trucks deployed (Figure 4.4). CNG consumption per kilometre and purchase price are major cost items and both appear to have a big influence on the attractivity of CNG technology, but the variance is not enough to unsettle the trend we described in the previous section. Consumption is the most volatile parameter as it largely depends on the driving skills of each driver, yet the average is far less uncertain across 40 trucks, each one driving more than 70,000 km a year.

The current state of the refuelling network and the future trend in oil prices appear to be the main drivers of the results. The differences in economic and environmental results with previous studies are therefore due to the integration of new parameters related to the transitional period of technology adoption. The paradox is therefore that the network of stations needs to be developed to reduce costs and emissions while at the same time oil is still too cheap compared to natural gas.

Figure 4.4 – Hypotheses and sensitivity analysis on the costs and benefits of converting trucks to CNG



Reading: From blue to red, a +10% uncertainty on purchase investment will reduce converted trucks by 87% for Step 2 in CNG (from 31 to 4).

4.3 Public incentives and policies

The previous section highlighted the conditions under which CNG can be a profitable option over diesel while cutting GHG emissions, i.e. long trips with short detours to reach refuelling stations, and big players with large fleet and a high level of commitment. The challenge for the State is therefore to promote NGV through an understanding of the real microeconomic determinants of the investment, while reducing GHG emissions. Public policies should clearly encourage the use of bioCNG: the objective is to make a mixCNG solution attractive compared to diesel and fossil CNG. A rise in carbon tax could make it possible to increase the attractiveness of bioCNG along with its ecological value, provided that the calculation method is changed.

The carbon trajectory used until now was defined by the French Finance Act 2018[8] and is incorporated into the price of diesel. Quick least-squares interpolation shows that it will reach €174.34/tCO_2 ton by 2030, which is still far below the recommended €250/tCO_2 to reach carbon neutrality by 2050 (Quinet et al., 2009). The drawback of the current carbon tax is that it is based on calculated TtW emissions. The TtW calculation does not consider any emission difference between biosourced and fossil gas, whereas the WtW calculation considers the carbon weight of each fuel. Here we modelled diesel, CNG and bioCNG price trajectories using the TtW and WtW hypotheses given in Figure 4.5. The WtW calculation increases the price of diesel and CNG while lowering the price of bioCNG. Therefore, emissions calculation methods influence policy design. A WtW carbon tax is a tool that can achieve both economic and environmental objectives by pushing bioCNG and mixCNG.

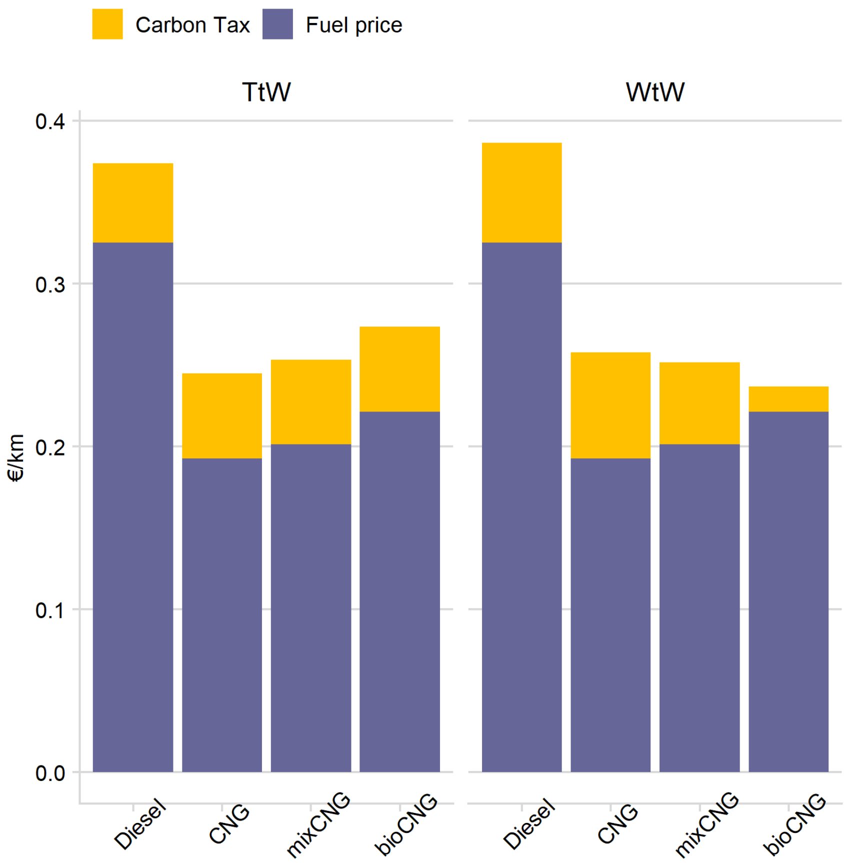
A steady-state tax of €50 per tonne is sufficient for all bioCNG scenarios to ensure a minimal GHG emissions reduction of 6% and for all scenarios to meet the Carbon Budget goal of limiting global warming to 2°C. More than the double, i.e. €102.31, would be required to achieve the same objective with a 30% bioCNG mix.[9] Note that the €50 tax is not high enough to allow all mixCNG scenarios to deploy gas HDV on the roads. In the long term, carbon price trajectories as planned in the Finance Laws imply a much higher carbon price compared to the steady state. A higher carbon price will make biogas and mixCNG more attractive compared to CNG and diesel, and it is likely than companies' levels of commitment and percentage emissions reduction would also be higher.

There is a huge discrepancy between the steady-state carbon price needed to reach environmental targets and the trajectory with a real and constrained starting point. Here, unlike other studies (Galbieri et al., 2018; Krupnick, 2010), we account for the transition period. Thus, the profitability of projects depends on the specific evolution of fuel prices but also on the carbon component specific to each country. The lack of visibility on this subject could lead agents to under-invest, hence the need for a clear framework for alternative fuels and clear long-term sustainable policies.

[8] https://www.senat.fr/rap/a17-113-1/a17-113-14.html

[9] While it may seem odd that the level of carbon tax required to ensure profitability is higher for mixCNG than for bioCNG, the reason that the difference between emissions per km multiplied by amount of carbon tax more than offsets the small extra cost of 10cts€/kg of biogas compared to CNG and, therefore, the extra cost of 6.67cts€/kg between bioCNG and mixCNG.

Figure 4.5 – 2020 fuel prices for CNG, mixCNG, bioCNG and diesel under TtW and WtW emissions computations



Reading: A kilometre by a bioCNG truck is worth 0.181 of fuel and 0.052 of carbon tax for on-road emissions or 0.015 per km of carbon tax for life-cycle emissions. Prices per kilometre encapsulate the consumption of different types of trucks and their detours.

In theory, a tax and a subsidy have exactly the same incentive effect if they are at same levels: the rational agent does not differentiate between an increase in the cost of one option through the tax or a decrease in the cost of another through the subsidy. In reality, carbon taxes have repercussions on society as a whole, destroying jobs in polluting sectors such as transport, or having very significant unequal impacts on the most fragile layers of society (Büchs et al., 2011). For a HDV, the additional investment cost between a CNG and a diesel is €23,847. Full compensation of this amount by the State could make practically every route potentially profitable (even though the price per km is still less for bioCNG than for diesel). Full reimbursement of the additional cost of purchasing a gas HDV would imply that the State has to subsidise up to 21.88%

of the truck purchase. In the median scenario (Central scenario x Step 1 x bioCNG), the minimum subsidisation required to convert at least one flow is 3.8% of the truck price, or 17.3% of the initial over-investment, i.e. €4,109. To ensure at least 1% of economic profitability for this flow would need a subsidy of 8.25%, i.e. €8,992 per truck. We found a significant influence of taxes and subsidies on company commitment levels and on numbers of CNG-converted HDVs in the model, in line with the conclusions of Morrison et al. (2018) and Hao et al. (2016) which indicate a 20% purchase subsidy to encourage investment. Similar levels are found in French law: the system put in place by France since 2015 provides a tax deduction equal to 40% of the cost price of the investment. This amount is deducted from the profit on a straight-line basis over the depreciation period chosen by the company to depreciate the asset via a reducing-balance method. This then comes to an amount of €14,388, i.e. 60% of the initial over-investment and 13.2% of the total purchase amount.

Government should move quickly to support commitment from major players in order to encourage the network to develop and ensure minimum profitability (Imran Khan, 2017). By the time the network is developed, the relative attractiveness of gas compared to diesel will have increased, and smaller players unable to reach Step 2 or Step 3 of commitment would be able to enter this market. Study of the transition period also shows that, counter to Heimer et al. (2017), a subsidy policy for the purchase of HDVs could be limited in time as the fuel price gap increases. Subsidies carry a cost burden for public budget, but this cost has to be weighed against all the co-benefits in terms of reduced public external costs. Table 4.5 summarises the different average gains over the three fronts considered in section 3.5.

A crucial comparison is the ratio of the amounts granted by the State through subsidies collected from households through taxes to the external costs avoided by the change from diesel to CNG. In the case of a 7% subsidy, the avoided costs are more than 300 times higher (0.26%) than the amount of the subsidy granted.

Compared to diesel, bioCNG averages 50% lower external costs when considering only pollution, climate change and noise. For CNG the gain is not automatic as CO_2 emissions are increased by 6.5% in the Central scenario, and in Step 2, unlike other steps, the decreases in noise and local pollution fail to offset this increase.

5 Conclusion and policy implications

This chapter sets out to determine the economic conditions under which it is both economically and environmentally beneficial to support switch to CNG for HDV. This investigation helps to explain why there has not yet been mass supply chain-wide energy transition in Europe. The model we deployed, based on data on French automaker Renault's real supply chain flows, estimated the profitability and conversion conditions of each route served. Even though the flows considered are mainly situated in highly-industrial northern France, the constraints of this fiercely competitive industry apply to practically all sectors. Detours to reach refuelling stations were identified as the key factor, influencing performances and unexpectedly pushing the CNG GHG emissions

Table 4.5 – Avoided external cost for central scenario over 5 years (2018-2022)

Fuel	Commitment step	Converted trucks	Total subsidisation (€) (8.25% subs.)	Avoided external cost *vs* diesel (%)	Ratio of subsidisation to avoided external cost
CNG	Step 1	32	€287,760	-4.45%	-0.31%
	Step 2	50	€449,625	+2.83%	+0.50%
	Step 3	81	€728,393	-6.82%	-0.25%
mixCNG	Step 1	31	€278,768	-5.33%	-0.26%
	Step 2	43	€386,678	-13.70%	-0.10%
	Step 3	76	€683,430	-20.41%	-0.08%
bioCNG	Step 1	4	€35,970	-12.60%	-0.08%
	Step 2	19	€170,858	-3.25%	-0.40%
	Step 3	70	€629,475	-20.46%	-0.08%

above diesel GHG emissions. We also showed that a WtW carbon tax or subsidisation was able to influence the uptake of partially-biosourced CNG to cut emissions by up to 76%, in which cases the external costs reduction in terms of air pollution, noise and GHG was 50% with bioCNG compared to the same route using diesel fuel.

Despite the relatively limited scope of our dataset, which is confined to an automotive supply chain in France, the results presented in this study are robust and significant enough to draw up some general policy recommendations. Barriers to NGV adoption—like the allied policy instruments—are common to many countries (Yeh, 2007). Here we compare the effectiveness of policies for incentivising NGV use for long-distance HDV, which can apply to countries at a similar stage of NGV adoption as in France. This study points to 4 policy recommendations to support the development of CNG as an alternative fuel for HDVs. Points two and three lead out from point one, while point four stands on its own:

(i) To reduce transport GHG emissions, public policies should encourage the use of biosourced or partially-biosourced CNG and deter from using entirely fossil-based CNG. Fossil CNG does not represent a viable low-carbon alternative to diesel for long-distance HDVs. In this study, comparative emissions for the same trips ranged between +0.01% and +9.6% for fossil CNG *vs* diesel but between -75.8% and -74.2% for bioCNG *vs* diesel. Efforts to decarbonise transport through the use of natural gas must therefore be based on biosourced natural gas, in accordance with the International Energy Agency recommendations (IEA, 2010).

(ii) Developing a local methanisation industry is a key prerequisite to drive a significant shift toward natural gas for goods transport. A right-sized methanisation infrastructure would ensure a sufficient supply of biosourced gas to meet growing demand while giving government and industry an opportunity to create jobs in the farming sectors that cannot relocate, and thereby help reduce dependency on imported fossil gas and oil (Balat and Balat, 2009).

(iii) Carbon tax should encompass the full life-cycle emissions (Well-to-Wheel instead of Tank-to-Wheel (TtW) emissions) of fuel in order to encourage biofuels such as biosourced CNG without actually raising the price of carbon. Taxing only the combustion part of natural gas (TtW) implies that CNG and bioCNG are taxed at the same level: there is no financial incentive for bioCNG over CNG. Based on the results of this study, fossil CNG emits more than diesel once consumptions of the real engines and refuel detours are taken into account, which means that a TtW carbon tax would counterproductively encourage the use of diesel over natural gas.

(iv) Governments should subsidise purchases of bioCNG HDV. Biosourced and partially-biosourced CNG are not yet profitable compared to diesel. The level of subsidy should be high enough to cover the potential fluctuation in oil and gas prices to create a steady and reassuring environment for industries to adopt bioCNG. Our model found that a minimum subsidy level set at 8% of purchase price would be sufficient to make the investment in CNG trucks profitable without companies having to engage massively in order to attain economies of scale. Incentivisations should be capped at 22%, which is the level that would fully subsidise the additional cost of purchasing a natural gas HDV. Subsidies could be made conditional on the use of bioCNG; this measure would be complementary with moves to extend the scope of carbon tax to life-cycle emissions.

Future research could usefully extend our methodology in a number of directions. Other modalities of real flows, such as congestion, road gradients, average speeds and payload, could all be refined. These parameters play a role in both the economic and ecological sides of the equation (Hausberger et al., 2009). This would make our already robust results even more accurate in terms of costs and emissions estimates, but would also allow us to refine and add parameters to our study of externalities. The logical extension of this study would be to reach out into other companies and countries and transborder trips, to gain a broader-picture perspective on multi-context economic situations.

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Appendix

> 118 minutes plus tard il se trouvait à 10 mètres de la gare Saint-Lazare, entrée banlieue, et se promenait de long en large sur un trajet de 30 mètres avec un camarade âgé de 28 ans, taille 1 m. 70 et pesant 71 kg qui lui conseilla en 15 mots de déplacer de 5 centimètres, dans la direction du zénith, un bouton de 3 centimètres de diamètre.
>
> Raymond Queneau, *Exercices de style*

4.A Price series

4.A.1 Carbon Tax

Carbon price trajectory has been decided by Parliament by the Law of Finance in 2018 until 2022. A basic linear approximation gives us the expected level of carbon tax in 2030. (Table 4.A.1)

Table 4.A.1 – Carbon Price Trajectories

	2017	2018	2019	2020	2021	2022
Carbon Tax (€/ton)	€30,50	€44.60	€55.00	€65.40	€75.80	€86.20

Note: The 2018 finance law only gives the trajectory until 2022, by the least squares method we can estimate that the value in 2030 of the finance law 164€.

4.A.2 Fuel and Gas Price

See table 4.A.2

Table 4.A.2 – Price Series for Gas and Fuel

DIESEL						
	2017	2018	2019	2020	2021	2022
TtW (kg CO_2 /L)	2.51	2.51	2.51	2.51	2.51	2.51
Carbon Tax (€/t)	€30.50	€44.60	€55.00	€65.40	€75.80	€86.20
Carbon Tax (€/kg)	€0.03	€0.04	€0.06	€0.07	€0.08	€0.09
Carbon Tax €/L	€0.08	€0.11	€0.14	€0.16	€0.19	€0.22
+Tax on Added Value	€0.08	€0.12	€0.15	€0.17	€0.20	€0.23
CENTRAL SCENARIO						
Price Diesel with carbon tax with TICPE discount (17 cts per litre)	€1.05	€1.10	€1.19	€1.27	€1.37	€1.43
BLACK DIESEL	€1.23	€1.39	€1.47	€1.55	€1.66	€1.72
GAZ						
	2017	2018	2019	2020	2021	2022
TtW (kg CO_2 /L)	2.78	2.78	2.78	2.78	2.78	2.78
Carbon Tax (€/t)	€30.50	€44.60	€55.00	€65.40	€75.80	€86.20
Carbon Tax (€/kg)	€0.03	€0.04	€0.06	€0.07	€0.08	€0.09
Carbon Tax €/kg	€0.08	€0.12	€0.15	€0.18	€0.21	€0.24
+Tax on Added Value	€0.09	€0.13	€0.16	€0.19	€0.22	€0.25
Gas Price	€0.74	€0.80	€0.83	€0.86	€0.89	€0.93

4.B Cost Breakdown

4.B.1 Cost Hypothesis Discussion

Material costs

- Duration of the commitment: 5 years
  Minimum duration of contractual commitment required by carriers, average transportation contract in the sector is 3 years. Since the risk is taken by the buyers of the truck, i.e. the carriers, this period is intended to compensate for any difficulties in resale if the market is not mature enough.

- Investment
  - Diesel truck €85 153 (French Road Council (CNR)[10].)
  - CNG truck: €109 000, catalogue price IVECO 2018

[10] Data available at : `http://www.cnr.fr/Indices-Statistiques/Longue-distance-EA/Referentiel-prix-de-revient`, consultation 02/2020

- Percentage of negotiation: 5% (steps 2 and 3)
  Discussions with other market players to negotiate discounts on behalf of carriers for large volumes. Construction technologies have evolved making possible some economies of scales, hence allowing for negociation. Name manufactors do no have anymore to take the truck out of the production line to install the tank thanks to the process' standardization.

- Resale Price : 10% of the new price for the CNG truck, 20 000
  euro o for diesel trucks after 5 years.
  This is one of the most controversial criteria of this decomposition. As the market is relatively recent in France (in 2012, i.e. 5 years ago, there were less than 150 gas-fired HDVs in France, source IVECO), resale is not yet organised and neither is the second-hand market. Most carriers therefore choose to consider that the truck will be unsellable after 5 years and that its value will be zero. It is not possible to prove them otherwise, but there are encouraging signs that interest in cheap trucks in 5 years' time will be relatively high:

  1. The Diesel ban in Paris will take place in 2025, shortly after the end of five contracts signed in 2019 or 2020. Carriers will therefore be keen to quickly buy gas trucks in order not to lose customers in the face of an anti-diesel wave
  2. The French truck resale market generally follows a 3-step process: new purchase in France, resale in 5 years in Eastern Europe, aged 8 to 10 years, the truck is resold in Africa. The Eastern European countries, Hungary (100% annual growth), Ukraine (400,000 trucks) and the Czech Republic (19,000 trucks), are already equipped with gas trucks, even if the network of stations remains largely insufficient (13, 143 and 324 stations respectively), all the evidence suggests that the network will develop in the coming years, thus creating opportunities.

- Registration certificate: €850 for Diesel, €5 for CNG (source CNR)

- Financing rate: 1% for all trucks (source: CNR)

- Methodology: Excel payment fonction (PMT) function to compute monthly material costs

Human Resources

- Monthly schedule: 220h

- Full-time equivalent required: one FTE per diesel truck is used as a reference, hourly cost €18.32.

- Overtime CNG: 7% (step 1 & 2), 4% (step 3)

  - At all stages of the project it is necessary to take into account that the gas network is not as developed as the network of traditional stations and that the autonomy of the LNG itself does not reach that of Diesel (1 full/week).
  - Same pricing for regular and overtime hours
  - We add the time to make the detour to reach the station, the time to fill the tank (longer than for Diesel), waiting time at the station. These three durations are estimated to be zero for the diesel truck, repeating less often, and requiring less time to fill the tank, the more numerous stations are less loaded for the diesel network. In addition to the above-mentioned detour, made at an average speed of 70km/h, there is a maximum of 10 minutes of filling time. Counting a single truck queue, we arrive at a full time of 20 minutes. We consider two full tanks per day in Step 1 and 2, only one in Step 3 (the full time in the factory before leaving is not counted, because it can be done by another driver).
    Over the month, these overtime hours are rounded up to +4% in step 3, to +7% in step 1 and 2.

Variable costs

- Fuel Price : the price of 2018 diesel is €1.1 per litre at the pump for professionals (excluding VAT, including TICPE discount of 17 cents per litre)
- Consumption: a sensitive hypothesis because it determines not only fuel savings but also CO_2 and other pollutant emissions directly related to combustion.
  - Only the difference between diesel consumption and gas consumption really matters. Consumption depends greatly on the journey, the conditions of the journey, the driver, the truck, etc. It is very difficult for shippers like Renault to obtain anything other than average consumption per carrier. These actual values can be compared with the values announced by the manufacturers, but without any more precision than that.
  - A reference work in this area is the "Equilibre" Report (Schnetzler and Baouche, 2019)ership with ADEME, published in 2018, which studies CNG and diesel trucks under the same conditions, differentiating consumption and emissions on different types of roads and traffic. On national roads, the majority of Renault flows, the difference between diesel and CNG consumption (kg/100km) is -8.14%, cross-referencing these data with consumption from tests with Renault carriers, we retain a difference of -7.58% in consumption kg/100km (29.7L Diesel/100km and 27kg CNG/100km). The price of gas per kg is also an important variable, even if the change in its price does not directly depend on an assumption. As the gas market is still young, price disparities between players are high and the need to make equipment profitable pushes gas companies to offer high prices to increase

marginal revenues per new customer. However, a contract with a large fleet allows it to increase its revenues more safely: the trading margin is thus much higher than in a transparent and competitive market. Steps 2 and 3 therefore benefit, for a fleet of about fifty trucks, from a negotiated price of gas at 72 cents per kilo against 75 cents in public price (`https://v-gas.fr/`), 80 cents per kg of gas is chosen in step 1, because experience shows that this is a price charged to carriers starting in this segment.

- Maintenance and tyres: +20% CNG vs Diesel/km for maintenance (source : Renault's and carriers expertise), nothing on tyres.
  Carriers advertise higher maintenance and tire costs for a gas truck compared to a diesel truck. The difference can range from 11 to 83%. No significant difference on the tyres except for the extra kilometres to reach the stations. We face a disparity in transporters' maintenance figures, justified by oils and parts different from diesel engines, which are rarer and therefore more expensive. We introduce an additional cost of 20% per km and question this cost in the sensitivity part.
  It contradicts Chandler et al. (2006) who found a 12% decrease in maintenance cost between Diesel and CNG buses in Washington. Semin (2008) found that due to absence of lead in CNG, piston rings last longer on a NGV, samely, oil changes frequence can be reduced by half.

4.B.2 Cost Breakdown — Step 2

See table 4.B.3

4.B.3 Cost Breakdown — Step 3

See table 4.B.4

4.C Counterfactual: Influence of detours on the results table

If we consider only the distance between point A and point B, without increasing the detour route to reach the refuelling stations, nor increasing overtime wage costs, we obtain the results of the following figure 4.C.1. The differences between steps 1, 2 and 3 come only from the negotiation of the price of the truck. All scenarios are profitable and above all it appears that CNG reduces GHG emissions by 0.2% compared to Diesel. We conclude that not taking into account the detours overestimates the economic and ecological interest of CNG.

Figure 4.C.1 – Trucks deployment, Cost and Emissions reduction without taking into account detour

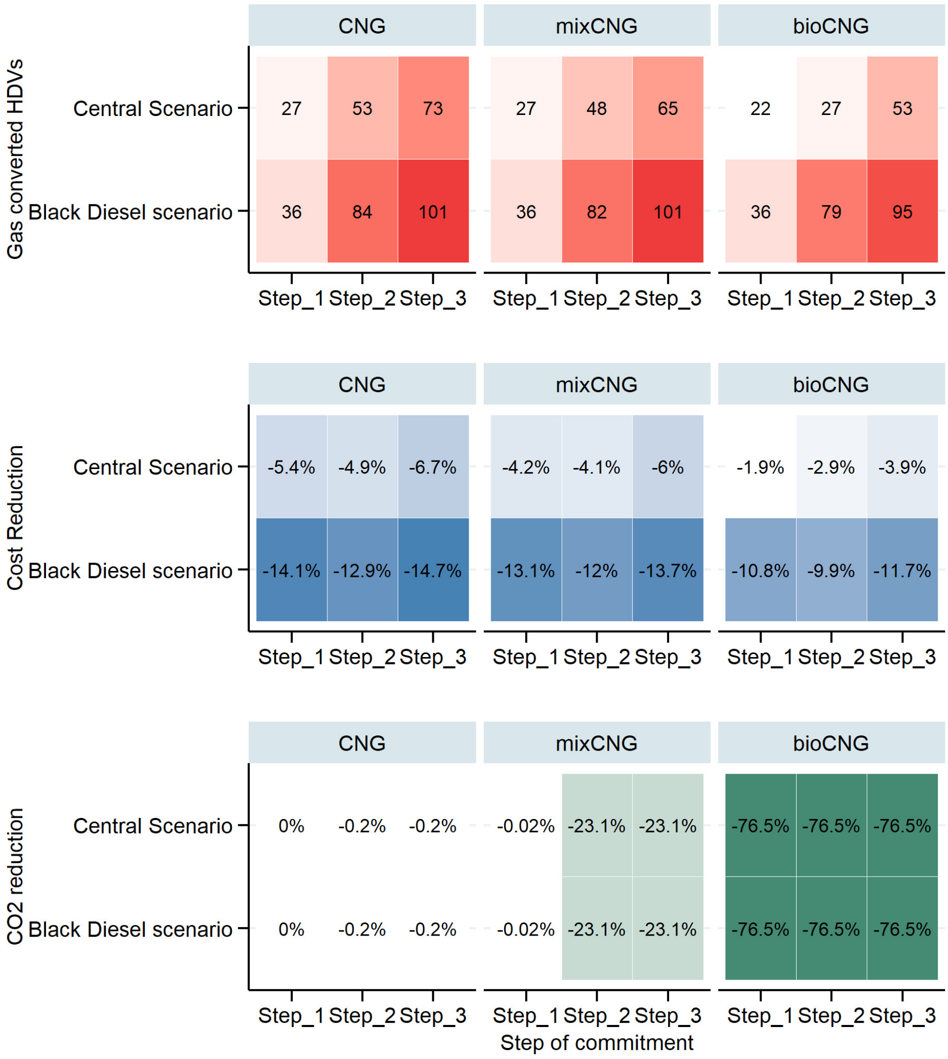

Table 4.B.3 – Cost Breakdown — Step 2

	Material investment			
	Diesel	CNG	mixCNG	bioCNG
Commitment duration	5 years	5 years	5 years	5 years
Biogas percentage	0%	0%	30%	100%
Investment	eur85153	eur103550	eur103550	eur103550
Negotitation (%)	0%	5%	5%	5%
Truck price after negotiation	eur85153	eur109000	eur109000	eur109000
License and registration	eur850	eur5	eur5	eur5
Truck buyback price after 5Y	eur20000	eur10900eur	eur10900	eur10900
Financing rate	1%	1%	1%	1%
Monthly cost of material	eur1145	eur1 593	eur1 593	eur1 593
Total cost of material (5Y)	eur68694	eur95574	eur95574	eur95574
	Human resources			
Monthly hours	220 h	220 h	220 h	220 h
Manpower (full-time equivalent)	1.00 FTE	1.07 FTE	1.07 FTE	1.07 FTE
Hourly wages	eur18.32	eur18.32	eur18.32	eur18.32
Total monthly cost	eur4029/mo.	eur4311/mo.	eur4311/mo.	eur4311/mo.
Total 5Y cost	eur241766.12	eur258689.75	eur258689.75	eur258689.75
	Variable cost			
Average fuel price over 5Y	eur1.2703/L	eur0.8631/kg	eur0.8931/kg	eur0.9631/kg
Consumption	29.7kg/100km	27.0kg/100km	27.0kg/100km	27.0kg/100km
Average fuel price/km	eur0.340/km	eur0.233/km	eur0.241/km	eur0.260/km
Maintenance	eur0.074/km	eur0.089/km	eur0.089/km	eur0.089/km
Tyres	eur0.039/km	eur0.039/km	eur0.039/km	eur0.039/km
eur/km average	eur0.490/km	eur0.361/km	eur0.369/km	eur0.388/km
eur/km average incl. detour	eur0.490/km	eur0.383/km	eur0.391/km	eur0.411/km

4.D Tax over-amortization

French Tax over-amortization for CNG HDV is €14,388 per truck. It has been passed in April 2015, also known as "Macron amortization in favour of investment" has been extended for clean trucks — such as gas or electric trucks — has been extended until 31/12/2019. The Clean Mobility Act should extend it until 2021. This depreciation makes it possible to deduct 140% of the vehicle's purchase value from its taxable amount for depreciation. This is therefore a gain equal to the value of the corporate tax applied on 40% of the value of the truck:

$$Value_{over-amortization} = 40\% \times Value_{New\ truck} \times Corporate\ income\ tax\ rate\ (33\%)$$

That is €14,388 per CNG truck worth€109,000. Certainty (subject to paying taxes, therefore making profits)

Table 4.B.4 – Cost Breakdown — Step 3

	Material investment			
	Diesel	CNG	mixCNG	bioCNG
Commitment duration	5 years	5 years	5 years	5 years
Biogas percentage	0%	0%	30%	100%
Investment	eur85153	eur103550	eur103550	eur103550
Negotitation (%)	0%	5%	5%	5%
Truck price after negotiation	eur85153	eur109000	eur109000	eur109000
License and registration	eur850	eur5	eur5	eur5
Truck buyback price after 5Y	eur20000	eur10900eur	eur10900	eur10900
Financing rate	1%	1%	1%	1%
Monthly cost of material	eur1145	eur1 593	eur1 593	eur1 593
Total cost of material (5Y)	eur68694	eur95574	eur95574	eur95574
	Human resources			
Monthly hours	220 h	220 h	220 h	220 h
Manpower (full-time equivalent)	1.00 FTE	1.03 FTE	1.03 FTE	1.03 FTE
Hourly wages	eur18.32	eur18.32	eur18.32	eur18.32
Total monthly cost	eur4029/mo.	eur4150/mo.	eur4150/mo.	eur4150/mo.
Total 5Y cost	eur241766.12	eur249918.11	eur249918.11	eur249918.11
	Variable cost			
Average fuel price over 5Y	eur1.2703/L	eur0.8631/kg	eur0.8931/kg	eur0.9631/kg
Consumption	29.7kg/100km	27.0kg/100km	27.0kg/100km	27.0kg/100km
Average fuel price/km	eur0.340/km	eur0.233/km	eur0.241/km	eur0.260/km
Maintenance	eur0.074/km	eur0.089/km	eur0.089/km	eur0.089/km
Tyres	eur0.039/km	eur0.039/km	eur0.039/km	eur0.039/km
eur/km average	eur0.490/km	eur0.361/km	eur0.369/km	eur0.388/km
eur/km average incl. detour	eur0.490/km	eur0.367/km	eur0.376/km	eur0.395/km

4.E Market growth in France and Europe

This is a good time to focus on the development of the CNG and its use by professional supply chains. Indeed, the context is more and more favourable to this technology which has now reached a degree of maturity that can be considered acceptable.

There is now a large variety of models and manufacturers available on the market (Iveco Eurocargo GNV, Iveco Stralis Euro 6 GNV, Mercedes Econic euro 6 GNV, Scania P-Series among others) freeing the captive consumer (Wang-Helmreich and Lochner, 2012).

Infrastucture is also at a turning point. Installing gas refuelling station and developing the fleet is truly a chicken and egg problem (Imran Khan, 2017) since even a small fleet requires a broad network of refuelling facilities.[11] No massive conversion to gas is possible without a large network while before this conversion to happen, fleet is not enough to make refuelling networks profitable with the risk of major players in the sector disengaging, as was the case in Canada (Flynn, 2002).

[11] See for instance, the Chinese LNG fleet outnumbered by 25 times by CNG vehicles while the infrastucture ratio dedicated to both of them is 1 for 2.

First sign is a rapidly growing Vehicle-to-Refueling-Stations index (VRI), that is to say the ratio of the number of vehicles to gas (in thousands), freight or passenger, on the number of station (Janssen et al., 2006). In Europe, there were 1,316,000 vehicles in 2016 (NGVA, 2017) for 4000 stations (C-L NG (IANGV, 2018)). This gives us an VRI of 0.33. (Table. 4.E.5). Janssen et al. (2006) conclude that the ideal value seems to be 1. 80 to 140 stations are open in France (source gaz-mobilité.fr) for about 14500 natural gas vehicles on the same date (IANGV, 2018). This gives an VRI of 0.1 to 0.16. The coverage in stations is already huge: supply exists, it will not grow any more until demand follows, id is the number of natural gas vehicles. According to Yeh's study (2007), France is in a critical period under an VRI of 0.2. Either the country manages to boost its demand and will quickly reach a ratio of 1 (e.g. Italy, Pakistan, Argentina and Brazil), or the market collapses as in New Zealand.

A second indicator measures the coverage of infrastructures, the quotient of the number of gas stations on conventional stations which is a driver of consummer's trust (Greene, 1998; Janssen et al., 2006). In Europe, the 4000 CNG stations represent 2.55% of conventional stations, France is at 1.34% (Table 4.E.5). Janssen (2006) estimates that a number of gas station between 10 and 20% of conventional stations is enough to overcome the *range anxiety*. Consumers no longer consider the station network as an obstacle to purchase out of fear of lacking fuel.

Worldwide in 2007 there were 5.1M natural gas vehicles for 9000 stations (VRI of 0.57) compared to 27.4M in 2018 (IANGV, 2018) for 32 211 stations (VRI of 0.85). In addition to the spectacular increase of 420% in vehicles and 240% for stations, there is a significant increase in the VRI, which is close to 1, a tutelary value for the harmonious development of the market (Janssen et al., 2006).

Table 4.E.5 – Gas Refuelling stations network is developing in France and in Europe

	France	EU
GNV Stations	149	3 958
Petrol Stations	11146	155000
GNV vehicles	14548	1316000

	VRI	Refuelling station ratio
France	0,10	1,34%
EU	0,33	2,55%

Source: IAGNV, gaz-mobilités.fr, statistica.fr, NGVA. The GRDF figures in 2016 of 453 stations opened in France appear to be completely out of step with all other sources

French and European gas vehicle market is maturing and is following the same rapid growth trajectories as the countries that preceded it in the adoption of CNG. These are good signs for a company or equipment manufacturer to embrace this trend. Even if starting later could be cheaper and easier, yet there is the risk of a market collapse, similar as what has been observed in New Zealand — a real free-rider issue.

4.F Plants coordinates

See Table 4.F.6.

Table 4.F.6 – Coordinates of the 6 plants studied

Plant	Longitude	Latitude
Sandouville	49.47668	0.29687
Le Mans	47.98248	0.18343
Douai	50.36298	3.03031
Flins	48.97707	1.85711
Batilly	49.1728	5.97311
Maubeuge	50.27155	3.90789

Conclusion

Ne serions-nous pas en train de signifier quelque chose ?

Samuel Beckett, *Fin de partie*

This dissertation broadly studies the fairness of the transition towards carbon neutrality. Both the academic literature and policymakers have been mostly focused on the effectiveness of policies to reduce greenhouse gas emissions and not enough on the distributional impacts. Reaching carbon neutrality will require deep changes of the economy that will impact both income and consumption patterns. In this dissertation, we assess the effectiveness of different policy measures to reduce emissions – targeting households or encouraging firm innovation – and the distribution of the costs among households from the consumption (use) and the income (source) side.

Two main threads run through the work gathered in this dissertation: the study transition period to reach net zero from the current carbon-intensive economy and the disaggregation of the effects to do so. The transition will likely be more abrupt than one would like and generate unequal effects that must be addressed. The adoption of the right behaviours and technologies by households and firms is not straightforward and needs careful attention. The first thread is then intertwined with the second one: mitigation impacts will be different depending on where households are on the income ladder — vertical heterogeneity — or where they live and other non-income dimensions — horizontal heterogeneity. The heterogeneity of impacts also exists on the production side, at the industry or firm level.

In the first part of the dissertation, we modelled the distributional impacts of net zero policy packages and concluded that a mitigation policy could be both effective and fair. While carbon pricing appears to be effective in reducing emissions and encouraging households to change their consumption, it is no silver bullet. It should be carefully designed and woven into a mix of complementary policies. A carbon price is more likely to be socially acceptable if it is paired with the recycling of the best part of its revenues to the low-income and vulnerable households and subsidies for investment in low-carbon technologies. Electric vehicles and thermal renovation will reduce emissions in the long term but need time to develop fully. Policy design faces two trade-offs, the first between emissions reduction and burden sharing and the second between the short and long-term effects.

In the second part of the dissertation, we have focused on the supply-side mitigation policies. The key issue is the incentive of firms to reduce emissions and innovate in a less carbon-intensive direction. We took a step aside from the environmental scope to analyse the more general question of the direction of technical change. The increase in the cost of inputs — which can be achieved through the rate of taxation — induces innovation in order to do without this input. However, technical change is protean, and each sector of activity reacts to price variations with its own mix of factor substitution and factor-specific innovation depending on the available technologies and the inputs on which it depends to a greater or lesser extent. We highlight again the importance of carefully designing a mix of policies to achieve the desired outcome and support the right technology.

What can we draw from these results? First, this dissertation does not conclude on whether it is possible to achieve carbon neutrality. It does not assess the future technological possibilities or the necessity to limit households' consumption. But what this dissertation shows is that it is possible to design and implement ambitious policies — taxes, subsidies, regulations that are both effective in reducing households emissions, encouraging innovation and limiting indirect emissions from production — that do not increase inequalities and can make the most vulnerable better off.

However, this dissertation has several limitations. It covers the climate transition and does not engage with the broader ecological transition to stay within all planetary boundaries, to limit the use of resources and to preserve biodiversity.

This dissertation focuses on distributional impacts and the effectiveness of policy measures, but leaves aside climate change damages. It has two consequences. First, we do not take into account the impact of climate change on current welfare — the impact it will have on the most vulnerable, often the poorest — and the benefits of avoiding current and future damages that symmetrically benefit more the poorest. Second, we do not question the socially optimal level of policies because its depends on the marginal damages of climate change. If damages are underestimated — leading to low-ambition policies — poorer households will be the most affected in the future. Consequently, this dissertation does not address adaptation policies, which are increasingly important as emissions rise.

The work gathered in this dissertation provides policy recommendations to implement fair mitigation policies, but it suffers from the usual biases of case studies based on a single country. In particular, a French carbon tax appears to be regressive, which does not seem to be generalisable to the whole of Europe, let alone beyond. Another limitation of our modelling work is that it is restricted to a mix of climate policies. In contrast, the Swedish example leads us to believe that a more global approach — considering the full tax system in particular — would allow us to better control the distributional impacts and social acceptability of the policy. The social acceptability of climate policies is also more complex than the focus of this dissertation on the use of the revenues generated and the distribution of costs.

The work initiated in this dissertation opens the way to fruitful future research avenues. This dissertation includes various methodologies and we have not exhausted the potential of any of them. MATISSE, the microsimulation model developed in the second chapter, should allow us to test the impacts of new policy packages including means-tested subsidies for low-carbon technologies, explicit carbon tax recycling mechanisms or labour tax cuts. One of the major avenues is to integrate source-side effects into the MATISSE model. Adding a layer modelling income and employment growth according to the sector of activity would further differentiate distributional impacts between households working in clean or dirty industries. This modelling requires assessing the sectoral pathway to decarbonise, including technical change. We could integrate the framework developed in the third and fourth chapters to model impacts on labour demand and wages. More broadly, the impact of mitigation policies on labour and workers needs to be further investigated.