Is green technical change skill-biased? A new growth accounting framework to disentangle the directions of technical change

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Abstract

The bias of technical change raises policy-relevant issues -– e.g. the impact of innovation on the distribution of income or energy-efficiency measures, investment in industry electrification — which are multi-factor and industry-specific. This paper develops a parsimonious growth accounting framework to compute the bias of technical change and disentangles factor-saving innovation from factor substitution at a disaggregated level. It does not require nesting CES functions nor estimating elasticities of substitution between factors. I build on Atkinson and Stiglitz (1969) to represent technical change as an increase in the technology menu available, shifting locally the production function. I apply this framework to industry-level data and answer key questions: What has been the bias of technical change across US and EU industries? Is green technical change skill-biased? Does an increase in the price of one factor spur specific factor-saving innovation? I first validate the model with only capital and labour and compare it to known technologies, then I extend it to fossil fuel, electricity, high and low skills labour. I find that fossil-fuel saving technical change correlates with skilled-labour saving technical change but has no impact on low-skills labour. I also find significant evidence of labour-saving technical change being induced by the rising cost of labour.

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1 Introduction

Technical change is the engine growth. In its simplest form it is Hicks neutral and applies to all factors the same. But we know that more often than not technical change is biased, favouring a factor over 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. Automation and other labour-saving innovation, including the new AI revolution, might impact the income distribution. The net zero transition plans on decreasing energy and material use without a recession. Redirecting and measuring the bias of technical change is thus a major policy issue. However, the bias of the technical change is not directly observable. It has proven a theoretical and empirical challenge to measure as the bias depends greatly on the form of the production function adopted.

The vast majority of the literature has adopted the well-behaved CES production function.[1] One needs indeed to constrain the functional form to estimate the bias of technical change and the substitution between factors (Diamond et al., 1978). However, the CES works best with two inputs and at either the macro or the micro-level, it is not well suited to several inputs and industry-level estimates. Theoretically, elasticities of substitution might differ at different level of aggregation (Houthakker, 1955; Oberfield and Raval, 2021) and differ in the short and long run (Brown and De Cani, 1963; León-Ledesma and Satchi, 2019). Empirically, estimating the elasticities of substitution at the industry level is tricky. Young (2013), following Antras (2004) method, and other studies[2], show that the estimates are inconsistent and range from -1 to 2 for a single sector.[3] What is more, the choice of the nested structure of the CES is not neutral and has an impact on the values of the elasticities of substitution. Without robust estimates of the elasticity of substitution at the industry level, let alone incorporate multiple inputs, one cannot rely on the CES function to estimate the bias of technical change.

In this paper, I am going back to an older literature and build on Atkinson and Stiglitz (1969) seminal paper to compute the bias of technical change without the CES assumption. I build a parsimonious growth accounting framework featuring n inputs that allows me to disentangle the different directions of technical change from each other and from factor substitution. I propose a proof of concept of this framework with capital and labour, using well-known technology examples in various industries in the United-States and European countries. I can then extend the framework to more inputs, including skilled and unskilled labour, fossil fuels and electricity. I focus on three applications in the form of questions: Is green technical change skills-biased? Does an increase in the price of one factor spurs specific factor-saving innovation? Can we forecast the evolution of factor shares?

The key intuition in Atkinson and Stiglitz (1969), further commented by Acemoglu (2015), is that technical change is *localised* – it improves on the techniques used at a specific capital-labour ratio and has spillovers limited to neighbouring ratios – and *biased* – the impact on the marginal product of capital differs from one capital-labour ratio to another. They ultimately consider that firms operate at a determined capital-labour k_0 ratio. The biased technical change is applied to a firm production function, modifying the capital-labour ratio at which it operates to k_1. The global production function, convex envelop of all firms' production function, is only affected around k_0 and k_1.

The intuition of the framework I develop build on this two properties of technical change – biased and localised. I will outline the model with capital and labour. Like Atkinson and Stiglitz (1969), I assume that firms (or industries) operate at a determined capital-labour ratio, fixed by the stock of capital (resulting from past investment) and a fixed supply of labour. Without further assumption, I can represent then represent production by a Leontief production function. I consider, as in the directed technical change literature (Acemoglu, 2002) and there I depart from Atkinson and Stiglitz (1969), that technical change increases the menu of technologies available. The minimal hypothesis is that two technologies, one purely labour-saving, the other purely capital-

[1] First of all the directed technical change models following Acemoglu (2002), taks-based models (Autor et al., 2003; Acemoglu and Autor, 2011), empirical estimation of the elasticity of substitution accounting for biased technical change (Antras, 2004; León-Ledesma et al., 2010), all rely on the CES function.

[2] See for instance Jin and Jorgenson (2010), Doraszelski and Jaumandreu (2018), Herrendorf et al. (2015), Raval (2019), Armanville and Funk (2003)

[3] Figure I.44 in Appendix I plots the different estimates for a same sector as proposed by (Young, 2013)

saving become available, and that the firm can combine them. These two new technologies can be represented as Leontief production as well, distortion into one direct of the initial production function. The new production of the firm is then the convex envelop of the two functions, a piece-wise linear function. This new production function allows for substitution, I can thus distinguish between the labour-saving and capital-saving components, and the substitution between the two factors. The global production function aggregating all firms production – and which can be a CES (see (Jones, 2005) – is then only affected around the initial and final capital-labour ratios.

Due to its simplicity, this framework is flexible and can operate on an arbitrary number of inputs. In a nutshell, the key intuition is that technical change can be represented as the distortion in a local Leontief production in two direction which aggregation gives a piece-wise linear function. The key theoretical result is that there is a unique decomposition of the bias of technical change and substitution to match specific changes in capital-labour ratio and factor prices. It allows to compute for any pair of observations (consisting of input and output) to compute the intensity of labour-saving and capital-saving technical change, as well as the contribution of technical change and substitution to the output-labour growth.

Using this framework, I compute the annual bias of technical change on industry-level input-output data. I use the KLEMS database, disaggregating inputs — capital, labour — and output per industry in Europe and the U.S. (Bontadini et al., 2023; Stehrer, 2021; Van Ark and Jäger, 2017; Timmer et al., 2007). I find that all European and U.S. industries exhibit both capital-saving and labour-saving technical change with a great heterogeneity between industries. However, the aggregate technical change is labour-biased, that is, the capital-saving technical change component is larger than the labour-saving one. I 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. I find that in Europe, the substitution between factors strongly complements technical change with a capital deepening of some sectors.

As a proof of concept, I can link trend-breaks in the bias of technical change to specific technologies or shocks of an industry, *e.g.* digital printers, shale gas oil, migration laws, the 2008 crisis. I show that my framework can describe technical change in a great number of contexts and performs better than a CES – that is with less uncertainty given that it does not depends on unstable estimates of σ – to explain the bias of technical change. In a later section, I further validate the relevance of my framework by comparing its predictive power on the evolution of the labour share. I find that my framework performs better than CES, Cobb-Douglas and Leontief production functions to forecast the labour share at 6 years, and even better on longer periods.

I then extend the number of inputs, including high, medium and low skills labour, capital, fossil fuel and electricity. I show that lower income European countries display energy-using technical change whereas high income countries tend to save on all inputs. I explore the correlations between the directions of technical change and find that fossil-fuel saving technical change (which can be innovation, processes, etc) is significantly correlated with skilled-labour-saving technical change (high skills and medium skills) but has no significant correlation with low-skills labour. An interpretation of this correlation is that green technical change is skills biased and reduces the demand for skilled labour. This evidence, based on various countries and industries data, could give a broader picture of the skills requirements of the net zero transition than the existing literature.

I finally find evidence confirming Hicks's hypothesis of price-induced innovation. I test for different specifications of Hicks's hypothesis on multiple datasets, from US and Europe. I find mixed evidence in some cases, but two clear results stand out. I 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). I also find an increase in the capital-using technical change intensity following an increase in the cost of labour. I highlight that my results hold for a varied sample of industries even though results are insignificant for many.

This paper contributes to three 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. The third is empirical determinants and consquences of the bias of technical change. The first contribution of my 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. I use Leontief production function and constrain the shape of the global production function using the factor shares. I 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). As Acemoglu (2015) explains, Atkinson and Stiglitz (1969) and thus my framework, can be microfounded by a task approach of the set of new technologies offered. By introducing a monopolistic competition for innovation, it is possible to represent the combination as a profit-maximising decision. The second contribution of my framework is then to estimate the bias of technical change at the industry-level. I show that multiple directions of technical change coexist, and amount to mostly capital-saving technical change. I relate the technical change bias time series that I compute to actual innovation to establish its validity. I use these estimates to test the causal relationship between price variations and the bias of technical change, and I find evidence of partial price-induced technical change in a sample of industries.

Finally, I contribute to more transversal and policy-relevant discussions on the bias of the net zero transition and the influence of prices on the direction of technical change. Policymakers might want to stimulate technical change — and economic growth — in a specific direction to limit inequalities or increase labour productivity. 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.[4]. A large literature has focused on the role of carbon pricing on innovation, let us cite Aghion et al. (2016) and Calel and Dechezlepretre (2016). For a more detailled review, refer to André et al. (2023); Popp (2019); Popp et al. (2010); Popp (2002) finding negative short term impact and ambiguous long term effect of carbon pricing on TFP. The skills content of the net zero transition is a more recent literature, Vona et al. (2015); Saussay et al. (2022); Consoli et al. (2016) show that green jobs require more skills than equivalent dirty jobs.

The remainder of this paper is organised as follows. In the next section, I discuss relevant literature. In section 3, I introduce the theoretical and the growth accounting framework for two inputs — capital and labour. Section 4 describes the database I use and the calibration of the framework. In section 5, I describe the trends in the bias of technical change in U.S. and European industries, and the complementarity of factor substitution and technical change. I extend the model in section 6 to explore the impact of green technical change on skills. In section 7, I present my test of Hicks' hypothesis and its results. In section 8, I forecast the evolution of the labour share and compare the results with a basket of classical production functions. Section 9 concludes.

2 Relevant literature

I 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. I contribute a parsimonious function to represent the bias of technical change and the dynamics of the labour share. It follows 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.[5]

[4]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)

[5]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)

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 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.

I also contribute to the literature estimating the bias of technical change on country- or industry-level data. This paper 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.[6] Jin and Jorgenson (2010) uses KLEMS data, and splits between the two types of technical change — the sum of autonomous and price-induced 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.

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).

[6] I 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.

3 Framework

This paper 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) at each period of time, I assume production takes place at a determined capital-labour ratio, allowing us to use Leontief production functions. It is important to remember that technical change is a shift in the production function when substitution is a movement along the production function. The key identifying assumption is that I consider that initially the firm behaviour is optimal at a determined capital-labour ratio, thus allowing me to represent production by a Leontief function (Atkinson and Stiglitz, 1969). I thus condition substitution on new technical change. Given the assumption on the menu of new technologies (labour and capital-saving), there is only one production function, convex envelop of two Leontief, that features a specific observation (output, capital, labour) and which first derivative in this point is the price of capital (profit maximisation condition). I can uniquely compute the directions of technical change explaining the evolution of output, inputs and prices.

In the following subsections, I present some theoretical results to construct a global production function by allocating inputs to two local Leontief production functions (section 3.1). Then I use these results to describe the technical change between two successive states of production in terms of their outputs, inputs and factor shares (section 3.4). Finally, I present a growth accounting framework that distinguishes technical change from capital deepening in the dynamics of value-added per worker (section 3.5).

3.1 Mathematical background

3.2 Leontief production functions

I define a Leontief production function, in intensive and extensive forms (Figure 1).

Definition 1. A Leontief function is a function F such as:

$$\begin{array}{rcl} F \quad : \mathbb{R}_+ \times \mathbb{R}_+ & \to & \mathbb{R}_+ \\ (K, L) & \mapsto & F(K, L) = Y = \min(A_K K, A_L L). \end{array} \tag{1}$$

It can be expressed relative to a certain point $Y_0 = F(K_0, L_0)$

$$\begin{array}{rcl} F: \quad \mathbb{R}_+ \times \mathbb{R}_+ & \to & \mathbb{R}_+ \\ (K, L) & \mapsto & F(K, L) = Y = Y_0 \cdot \min\left(\frac{K}{K_0}, \frac{L}{L_0}\right) \end{array} \tag{2}$$

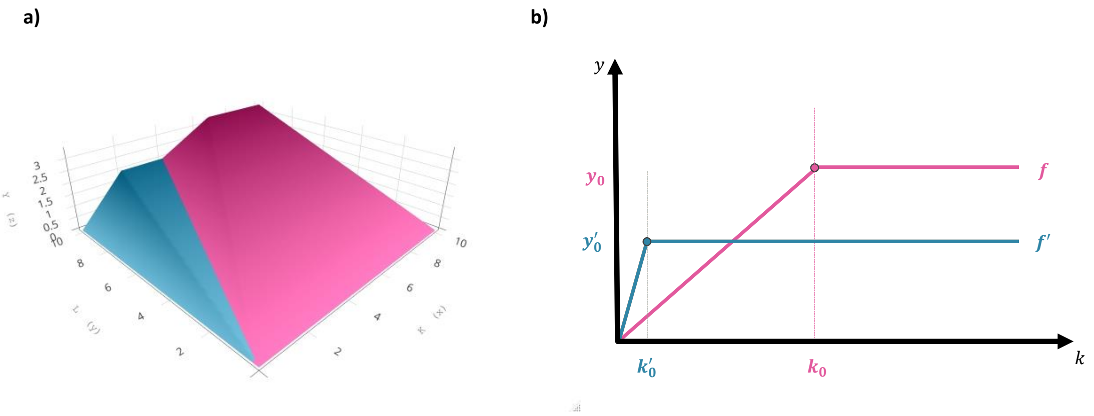
The intensive Leontief production function, in a framework (y, k), is then:

$$\begin{array}{rcl} f: \quad \mathbb{R}_+ & \to & \mathbb{R}_+ \\ k & \mapsto & y = y_0 \cdot \min\left(\frac{k}{k_0}, 1\right) \end{array} , \tag{3}$$

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 (Optimal ratio)**.** A Leontief function has a *optimal 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 *optimal point* is the output per worker y_0 than the function can reach in the capital per worker k_0.

Figure 1: Two Leontief prodution functions in extensive (a) and intensive (b) forms



3.3 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.

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.

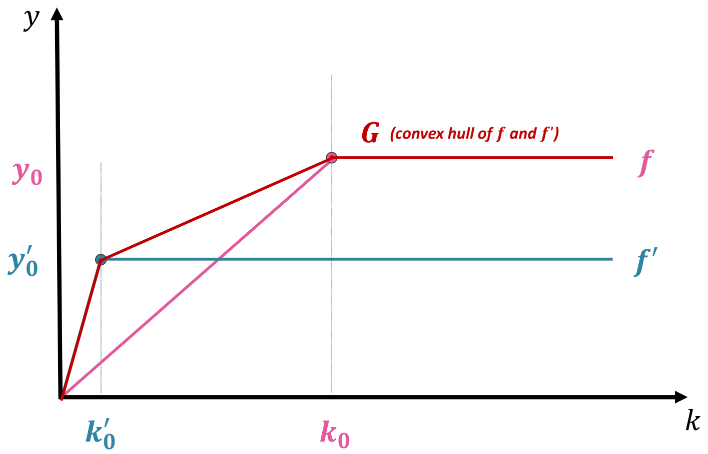
Proposition 1. *Let us have two Leontief production functions without one dominating the other. I can build a global production function which is the convex envelop of the two local production functions. Depending on the ratio of capital to labour, inputs are allocated either to one function or to both.*

I need two lemmas to demonstrate Proposition 1 (Lemmas' proofs are available in appendix 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.[7]

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.

[7] If they don't dominate themselves, the convex envelop is not a Leontief, there is a domain in which there is a possibility of substitution between factors.

Figure 2: Two Leontiefs production functions f and f' and their convex envelop G



Lemma 2 From two local Leontief production functions F and F' that do not dominate each other, I can construct a global function G by efficiently allocating inputs $(\bar{K}, \bar{L})$ to these two functions:

$$G\left(\bar{K}, \bar{L}\right) = \left[\begin{array}{cc} \max_{(K,K',L,L')} & F(K,L) + F'(K',L') \\ \text{with:} & \left\{ \begin{array}{l} K + K' \leq \bar{K} \\ L + L' \leq \bar{L} \end{array} \right. \end{array} \right]. \tag{4}$$

1. Function G is the convex envelop of F and F', it can be expressed as follows:

$$G = \left\{ \begin{array}{rl} F'(\bar{K}, \bar{L}) & \text{if } \bar{k} < k'_0 \\ F'\left(\bar{L}\frac{k_0(k_0-\bar{k})}{k_0-k'_0}, \bar{L}\frac{k_0-\bar{k}}{k_0-k'_0}\right) + F\left(\bar{L}\frac{k_0(\bar{k}-k'_0)}{k_0-k'_0}, \bar{L}\frac{\bar{k}-k'_0}{k_0-k'_0}\right) & \text{if } k'_0 < \bar{k} < k_0 \\ F(\bar{K}, \bar{L}) & \text{if } k_0 < \bar{k} \end{array} \right. . \tag{5}$$

   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 (5) is the competitive market allocation.

Proof of Proposition 1

Proof. I want to build a global production function using the two local production functions at my disposal. From Lemma 1, no single function performs better in every point. I can build a global production function G defined as in equation (5), which maximises output by allocating inputs to one or both of the local production functions (see Lemma 2). This function is the convex envelop 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. □

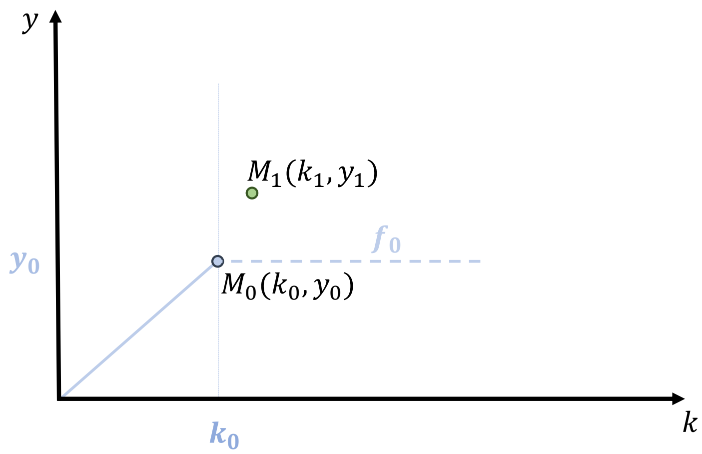
3.4 Application to technical change

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. I then obtain the global production function by allocating inputs to one or two of these functions to reach the convex envelop of two functions. From the proposition 1 I know how to build these functions. I present the construction of the framework in 3 steps.

3.4.1 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, the production is represented by the point M_0 and f_0, the intensive form of the production function F_0.

Figure 3: Step 1 — Starting situation: two points and a production function

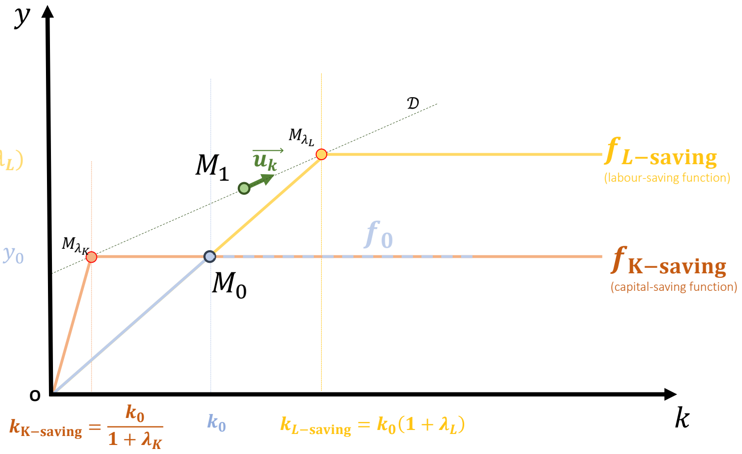


Factors shares of capital and labour are expressed as: α_{K_0} and α_{L_0} defined as $\alpha_K = rK/Y$ with r the real price of capital, likewise $\alpha_L = wL/Y$ with w the real wages. I assume perfect competition, all factors are paid their marginal products.
Production at time $t = 1$ is Y_1, with 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).
If as in figure 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 $t = 1$.

3.4.2 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 4).

Figure 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 B

Factor-saving functions The two factor-saving functions are expressed as follows:

$$F_{\lambda_K}(K, L) = Y_0 \min\left(\frac{K}{\frac{K_0}{1+\lambda_K}}, \frac{L}{L_0}\right) \tag{6}$$

and

$$F_{\lambda_L}(K, L) = Y_0 \min\left(\frac{K}{K_0}, \frac{L}{\frac{L_0}{1+\lambda_L}}\right). \tag{7}$$

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 optimal points are $M_{\lambda_K} = \left(\frac{k_0}{1+\lambda_K}, y_0\right)$ and $M_{\lambda_L} = (k_0(1+\lambda_L), Y_0(1+\lambda_L))$.[8]

I 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 $F_{\lambda_K}(K, L)$ (6) is capital-saving for any $\lambda_K > 0$. Its optimal ratio is $\frac{K_0}{L_0}\frac{1}{1+\lambda_K}$ against K_0/L_0 for F_0. The decrease of this optimal ratio means, according to Hicks' definition, that the technical change from one function to the other is capital-saving.

Similarly, the function $F_{\lambda_L}(K, L)$ (7) is labour-saving with respect to F_0 for any $\lambda_L > 0$ since its optimal 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 I identify the parameters λ_L, λ_K with two conditions:

1. I 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 envelop of $F_{\lambda_K}(K, L)$ and $F_{\lambda_L}(K, L)$. I assume that F_1 is distinct from the two factor-saving functions.[9] 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 (5). In intensive framework (2D),

[8] For the sake of simplicity, the same notations refer to the equivalent points in the 3-dimensional extensive space
[9] Without loss of generality. The demonstration is easily adaptable if F_1 is equal $F_{\lambda_K}(K, L)$ or $F_{\lambda_L}(K, L)$.

this $\mathscr{H}$ is represented by the the line $\mathscr{D}$ (Figure 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.[10]

2. The framework accounts for factor shares. I assume perfect markets, which translates into capital cost r and wage w equating F_1 first derivatives at M_1:

$$\frac{\partial F_1}{\partial K} = r_1 \text{ and } \frac{\partial F_1}{\partial L} = w_1. \tag{8}$$

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 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,

$$\begin{vmatrix} 1 & 0 & \dfrac{K_0}{1+\lambda_K} \\ 0 & 1 & L_0 \\ r_1 & w_1 & Y_0 \end{vmatrix} = 0. \tag{9}$$

Lambdas expressions Hence,

$$\lambda_K = \frac{-Y_0 + r_1 K_0 + w_1 L_0}{Y_0 - w_1 L_0}. \tag{10}$$

Likewise,

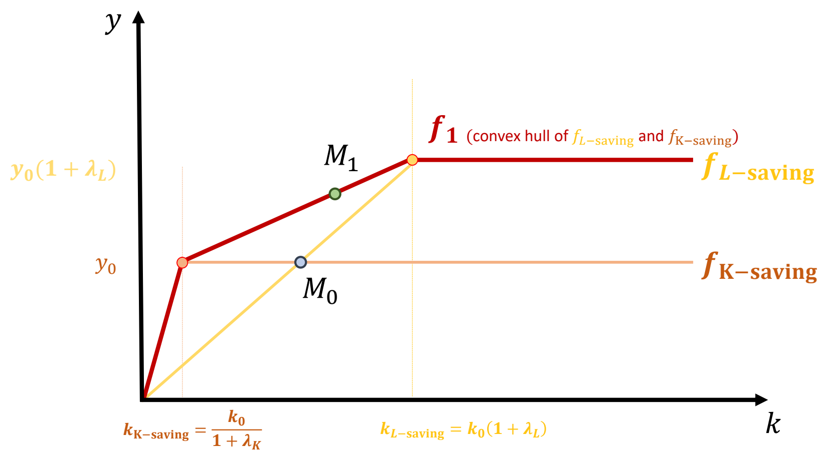
$$\lambda_L = \frac{-Y_0 + r_1 K_0 + w_1 L_0}{Y_0 - r_1 K_0}. \tag{11}$$

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*.[11]

3.4.3 Step 3: Inputs allocation

I apply the Proposition 1 to this situation: I 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).

Figure 5: Step 3 — Inputs allocation



[10] 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, I work in a plane obviously containing all the aforementioned points.

[11] Note that the meaning of the bias refers to Hicks (1932). It is equivalent to Acemoglu (2002) but I do not define factor-augmenting technical change.

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:

$$\begin{cases} \beta_K \cdot \dfrac{K_0}{1+\lambda_K} + \beta_L K_0 = K_1 \\ \beta_K L_0 + \beta_L \cdot \dfrac{L_0}{1+\lambda_L} = L_1 \\ F_{\lambda_K}\left(\beta_K \cdot \dfrac{K_0}{1+\lambda_K}, \beta_K L_0\right) + F_{\lambda_L}\left(\beta_L K_0, \beta_L \cdot \dfrac{L_0}{1+\lambda_L}\right) = Y_1. \end{cases} \tag{12}$$

To ensure that the production function contains the point M_1 (point 1), I define the input allocation between the two factor-saving production functions as the solution of equation (12). It emerges that the allocation of resources (β_K, β_L) between the two production functions is given by:

$$\begin{pmatrix} \beta_K \\ \beta_L \end{pmatrix} = \begin{pmatrix} \dfrac{(1+\lambda_K)(-K_1L_0 + K_0L_1(1+\lambda_L))}{K_0L_0(\lambda_L + \lambda_K + \lambda_L\lambda_K)} \\ \dfrac{(1+\lambda_L)(-K_0L_1 + K_1L_0(1+\lambda_K))}{K_0L_0(\lambda_L + \lambda_K + \lambda_L\lambda_K)} \end{pmatrix}. \tag{13}$$

3.4.4 Summary

I 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),[12]
- 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 (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.

3.4.5 Successive iterations

I assume that in each period I 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, the firm "forgets" about the two factor-saving Leontief and I use the point M_1 as the optimal point of a new Leontief function. I 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.

I 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 I start from a new Leontief function at each period, there is no path dependence in this framework.[13]

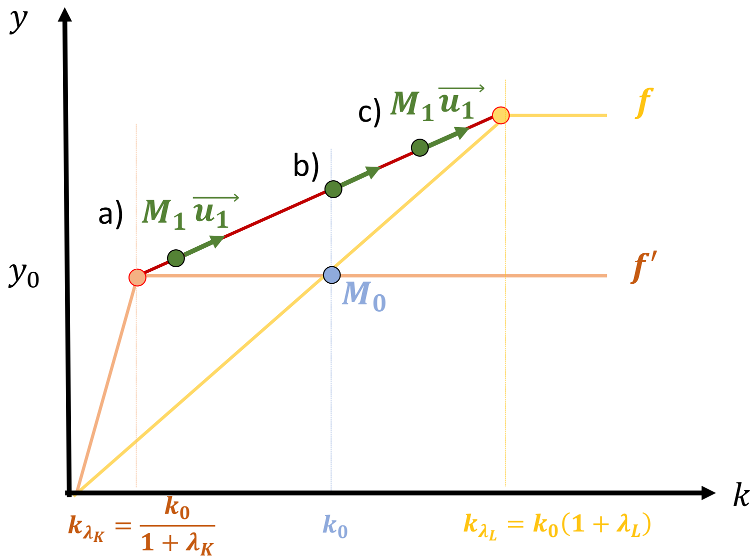
[12] The choice of λ to represent the intensity of technical change in a certain direction is consistent with the nomenclature of Klump et al. (2007) where the λ represent the curvature of the Box-Cox transformation and the speed of a labour- and capital-augmenting technical change.

[13] I can interpret in several ways the absence of path dependence. I 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, I 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.

3.5 Growth and technical change accounting

I can easily see in equations (10) and (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 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 via the βs (eq. (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 I can have some substitution between L and K in my model.

Figure 6: Substitution versus Technical change

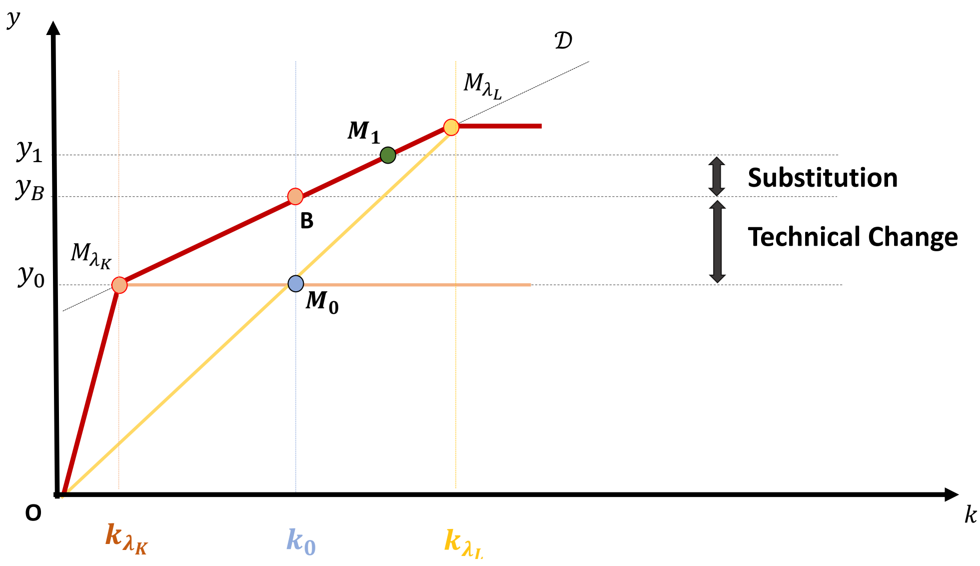


Note: Three situations a, b and c where M_1 is more or less capital-intensive give the same λ_L and λ_K, that is the same technical change bias. The phenomenon leading from situation *a* to *b*, *a* to *c*, or *b* to *c* is not technical change but pure capital deepening.

The function f_0 is used at the point M_0, and the technical change explains how the production shifts to M_1. I explain the growth of output per worker y_0 to y_1 due to technical change and substitution between factors. I call B the intersection point between the vertical line in $k = k_0$ and the line $\mathscr{D}$. (Figure 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. I 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 optimal ratio k_{λ_K} and k_{λ_L}. This slope is determined using the factor share to calibrate the model in equation (8). It plays the role of the elasticity of substitution in CES production functions. I am able to disentangle technical change and substitution because I take this parameter into account to build the framework.

Figure 7: Growth accounting decomposition for output growth in an intensive framework



I can express the two conditions using the equation of $\mathscr{D}$:

$$\mathscr{D} : y \mapsto \frac{y_0}{k_0} \frac{\lambda_L(1+\lambda_K)}{\lambda_L + \lambda_K \lambda_L \lambda_K} \cdot k + y_0 \frac{\lambda_K(1+\lambda_L)}{\lambda_L + \lambda_K \lambda_L \lambda_K}. \tag{14}$$

The technical change contribution is:

$$\begin{aligned} \frac{y_B - y_0}{y_0} &= \frac{(\lambda_K + \lambda_L + 2\lambda_K \lambda_L)}{(\lambda_K + \lambda_L + \lambda_K \lambda_L)} - 1 \\ &= -1 + \frac{r_1 K_0}{Y_0} + \frac{w_1 L_0}{Y_0} \\ &= -1 + \frac{p_{K1} K_0}{p_{Y1} Y_0} + \frac{p_{L1} L_0}{p_{Y1} Y_0} \\ &= -1 + \alpha_{K0} \frac{p_{K1}}{p_{K0}} \frac{p_{Y0}}{p_{Y1}} + \alpha_{L0} \frac{p_{L1}}{p_{L0}} \frac{p_{Y0}}{p_{Y1}}. \end{aligned} \tag{15}$$

The capital deepening contribution is:

$$\begin{aligned} \frac{y_1 - y_B}{y_B} &= \frac{y_1}{y_0} - \frac{(\lambda_K + \lambda_L + 2\lambda_K \lambda_L)}{(\lambda_K + \lambda_L + \lambda_K \lambda_L)} \\ &= \frac{Y_1 L_0}{Y_0 L_1} - \frac{r_1 K_0}{Y_0} - \frac{w_1 L_0}{Y_0} \\ &= \frac{L_0}{Y_0} \left(\frac{Y_1}{L_1} - \frac{r_1 K_0}{L_0} - w_1 \right) \\ &= \frac{y_1 - r_1 k_0 - w_1}{y_0} \\ &= \frac{r_1 (k_1 - k_0)}{y_0} \end{aligned} \tag{16}$$

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%. A change in the prices of the factors leads to technical change, wile a change in the factor ratio is capital deepening. It means that there is some induced technical change baked in the model itself. We study this relationship in detail in section 7.

4 Data

To put my framework to the test of observations, I 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 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, I 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. I derive input share as the share of the cost of one factor. Prices for each factor are included in the table for each industry. I use current values as it allows me to express input share easily without the usual bias from economic deflators such as Laspeyres, Paasche or Fisher. Since I use only two inputs — capital K and labour L —- I 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, I 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. I 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, I compute prices as the ratio of compensation and quantities. I check that this method provides the right price as indicated for output and intermediate output in the database. I compute value-added for each industry. I 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. I only keep series from the v2017 when the industry for a country is not available in the 2021 database (see Table 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. I check along the process that I get similar trends in prices, quantities and technical change indexes for the comparable industries within EU+ KLEMS and U.S. KLEMS database.

In section 5.2, I 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. I present trends in technical change across the 3 databases for European countries for two sectors in the appendix D, figure D.10 and figure D.12.

Table 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.

For section 6, I use Eurostat country industry-specific energy consumption (Table env_ac_pefasu) from 2000 to 2022. I reaggregate the 23 products into four categories: natural gas, heating fuel, crude oil, automotive fuel, LPG, coal and electricity. I exclude the other energy source (wood, nuclear fuel). I use Eurostat data to get annual industry-level prices (inclusive of taxes) for electricity and natural gas (nrg_pc_203 and nrg_pc_205) from 2007 onwards. I use the European Commission Weekly oil bulletin to get country specific prices for heating fuel, automotive fuel and LPG (2005 onwards). For coal, I use the FRED time series "Australia, U.S. Dollars per Metric Ton, Annual, Not Seasonally Adjusted" (PCOALAUUSDA) that is are representative of the global market. I use the dollar euro exchange annual dataset by the European Central Bank(EXR.A.USD.EUR.SP00.A). Wood prices given by the European Commission (Wood as a source of energy) only span 2005-2015 and cover only wood particles. I then exclude wood from the data. I aggregate all fossil fuels (all energy except electricity). I recompute a chained volume index and a price index for electricity and fossil fuel.

5 Proof of concept: a technical change overview oer industry in the U.S. and Europe

I apply the framework detailed in section 3.4 to the KLEMS databases. I compute λ_L, λ_K, β_L and β_K per industry with equations (10, 11, 13).

In a nutshell, I find great heterogeneity between industries in terms of labour-saving and capital-saving technical change. Most industries have been relatively more capital-saving in the 90s and increasingly labour saving since mid 2010s (US and EU). It partly answer to Blanchard et al. (1997): the fall is the labour share is not explained by labour-saving technical change. The growth of output per worker during the 90s is partially driven by capital-deepening ($\approx$50%) and partially technical change ($\approx$50%). Part of what has been classified as labour-saving technical change in the literature is thus capital deepening.

More importantly, I identify a few key technologies for which we know the bias of technical change and check that my framework gives the same results. The most important is the realase in 2001 of a three-times more efficient digital printer for the printing industry, a purely capital-saving innovation. Likewise, the shale gas revolution in the US leads to both capital-using and labour-using technical change compared to conventional oil. Anti-immigration laws in the US coincide with labour-saving technical change, a movement that I do not observe in Europe.

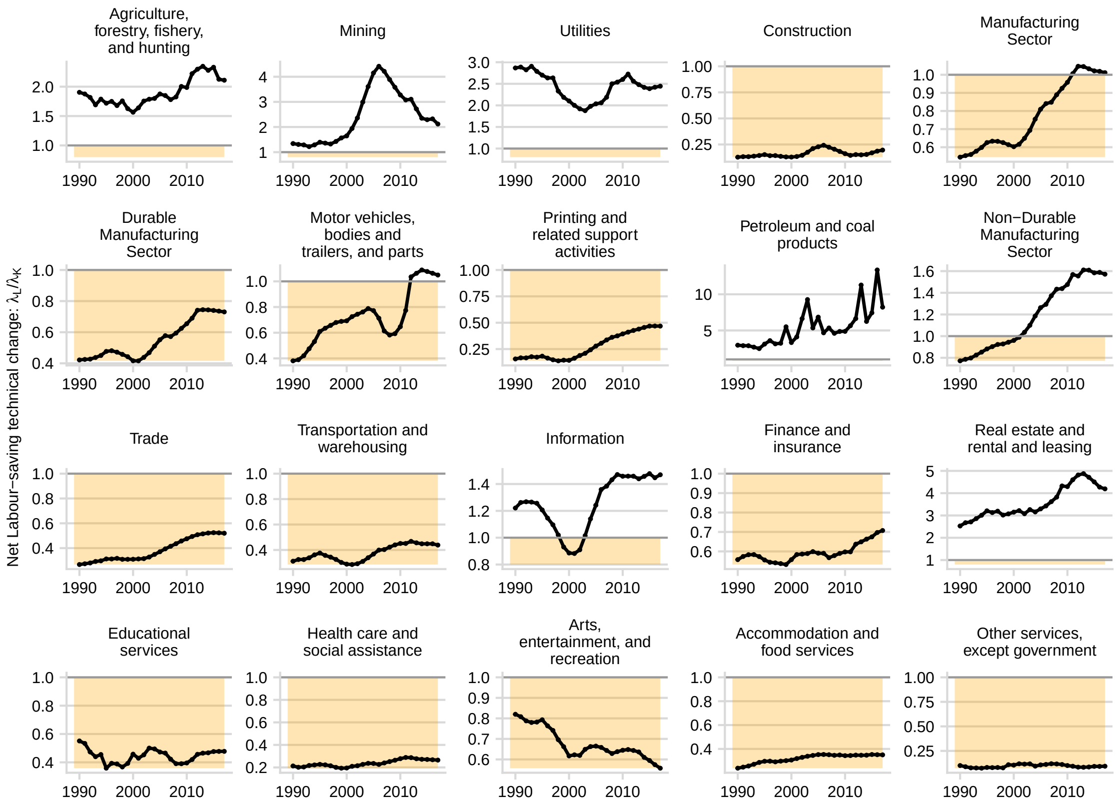
5.1 United-States Technical Change

Figure 8 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).[14]

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.

I will focus on some industries to link the dynamics of the relative direction of technical change to specific technologies and innovations. I will use the growth accounting framework to distinguish technical change from substitution of capital for labour.

Figure 8: 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 C.8 shows that the trends of this indicator are identical on annual data or with a rolling average period of 3 or 5 years.

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 8). After the economic crisis in 2008, technical change has been factor-using, showing negative λs: the industry under-utilised its capital and

[14] I 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.

labour inputs due to the demand shortfall, which shows up in my 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.

Indeed, manufacturing output per worker increased rapidly between 1995 and 2005, then slowly up to 2019 (Table 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).

Table 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.

Automotive industry By the end of the 90s, U.S. plants had already almost 100% automated bodywork[15] 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, 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. I 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 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.[16] 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

[15]Definition: the bodywork is "the main outside structure of a vehicle, usually made of painted metal", Oxford Dictionary.

[16]Production increased by +54% between 2007 and 2008, +74% between 2008 and 2009 (EIA Data).

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 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 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[17] 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 my 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 8). The labour-saving trend is greater than in almost all other sectors. Along with Herrendorf et al. (2015) I 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 C, Table C.3).

Gallardo and Sauer (2018) provides an overview of labour-saving innovations in the agricultural sector. I 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 — I am 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.

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).

[17] They are not shown in figure 8. They include: Management of companies and enterprises (55); Administrative and waste management services (56); Professional, scientific, and technical services (54).

Printing industry The publishing industry requires heavy investment, especially in printing presses. With the printing industry, I 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[18] 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 C, Table 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 C, Table 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 C, Table C.4). The second half of the 2000s saw a strong net capital-saving technical shift (Figure 8) that can be linked to the rise of search engines (Google was founded in 1998) and the launch of Web 2.0 in 2004.

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 C.9).

For each pair $\lambda_{K,L}$ — the intensities of technical change — I compute the allocation of inputs to the factor-saving functions: $\beta_{K,L}$. For 69% of the observations, I obtain a pair of positive β. This means that my model does not provide a satisfactory representation of technical change for 30% of the observations. Indeed, a negative β means that I use a production function with negative inputs — which is, of course, physical nonsense. I can put forward two hypotheses. The first is that I am 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 my 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[19] suggests that the problem is not the intensity of technical change, but that I am capturing a broad effect of "technical change" on fuzzy data in a world where the *ceteris paribus* is just an illusion.[20]

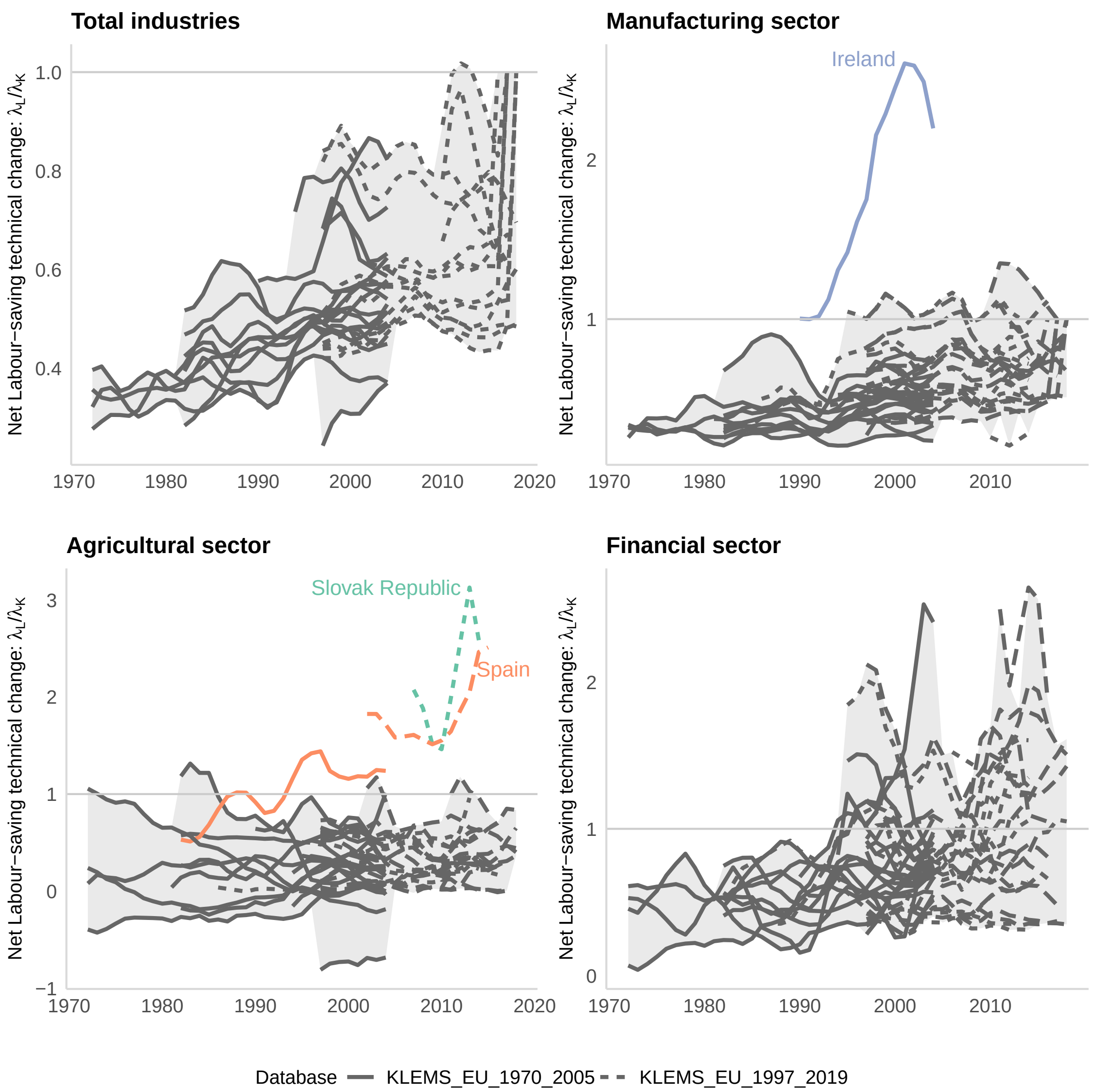
[18] The Four-Colour Indigo Press, followed in 2001 by the Colour Docutech 2060 has doubled the production per minute (Hargrave, 2013; Dunn et al., 2001).

[19] Note that the trend of the λ_L/λ_K ratio are unchanged if I exclude these points. Similarly, the analyses in the following sections are unchanged if I exclude negative βs.

[20] 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.

5.2 European Technical change

Figure 9: Net Labour-saving technical change (λ_L/λ_K on 4 industries for KLEMS EU+ (two databases))



At the national level, European economies are still predominantly capital-saving,[21] but the figure shows a clear trend towards increasingly labour-saving technical change from 1970 to 2019 (Figure 9). 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 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

[21]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.

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 paper. 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.[22] 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 I witness a labour-saving in my 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 D, Figure D.11) – and sometimes both negative – the resulting technical change is small but net-labour saving.[23] 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.

[22] 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.

[23] 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.

5.3 Discussion

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 9) and the U.S. since 1970, and there does not seem to be a major episode of substitution across the continent.

My 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[24] 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 technical change can coexist, so we are not in contradiction with the theoretical models since my λs represent annual directions of technical change.

5.4 Comparison to a CES production function

To further validate my framework, I compare the bias of technical change estimated by a CES production function. I use the work by Antras (2004). I then compare the measured bias of technical change for the Printing industry and compare it to my framework.

The CES production function is:

$$Y = \left(\alpha(B_tK_t)^{\frac{\sigma-1}{\sigma}} + (1-\alpha)(A_tL_t)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}, \tag{17}$$

with K_t and L_t the quantities of capital and labour, at the prices R_t and L_t respectively. σ is the elasticity of substitution. A and B are the factor-augmenting component:

$$B_t = B_0e^{\lambda_K t} \quad \text{and} \quad A_t = A_0e^{\lambda_L t}$$

It comes from profit maximisation, that

$$\ln\left(\frac{K_t}{L_t}\right) = \delta + \sigma\ln\left(\frac{W_t}{R_t}\right) + (1-\sigma)(\lambda_L - \lambda_K),$$

δ is a constant, and $(\lambda_L - \lambda_K)$ is the bias of technical change.

I use Young (2013) elasticities of substitution for the printing industry (323) (Table 3). First, it illustrate the difficulty to estimate consistent elasticities at the industry level. Note that Young include the Antras (2004) definition of bias as to not bias its estimates.

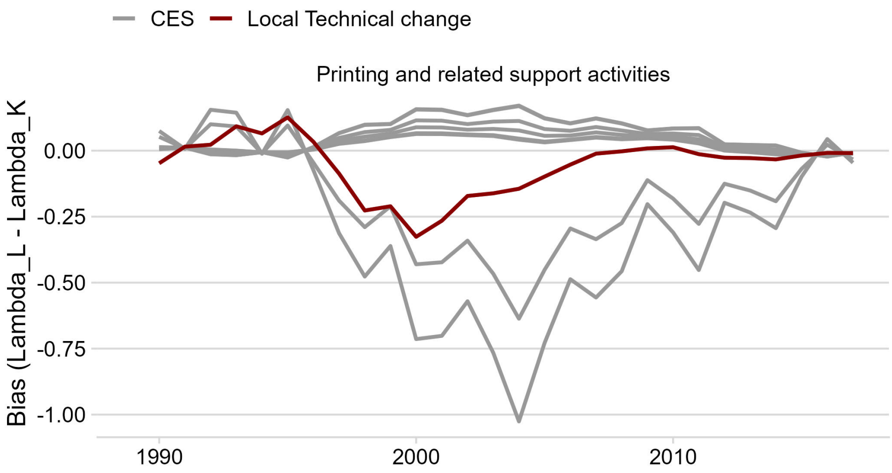
Table 3: Elasticities of capital-labour substitution from Young (2013)

GIV	OLV	GMM
0.352	0.196	0.503
1.213	1.126	0.507
-0.013	-0.05	

Figure 10 shows that the inconsistent estimates of the elasticities of substitution translates into inconsistent estimates of the bias of technical change. As we know the value of the bias should be negative around 2001-2002 to reflect the new Colour Docutech 2060 printer (increase from 20 to 50 sheets per minute), we could conclude that the elasticity of substitution is likely to more than one to match the expected bias. We also conclude that my framework allows to pinpoint the value of the bias without as much uncertainty as the CES in this case.

[24] If capital and labour as supposed to be gross estimates, then labour-augmenting means capital biased and labour-saving.

Figure 10: Labour-capital bias of the printing industry in the US (1989-2019)



Note: A positive value of the bias indicates a labour-saving technical change (labour-saving trumps capital-saving), a negative value indicates capital-saving technical change (or labour-using). Elasticities of capital-labour substitution from Young (2013). The red line represents the bias of technical change from my framework, the grey line represents the various bias of technical using each elasticity in table 3.

6 Is green technical change skills-biased?

The skills in the net zero transition is a topical question. A recent empirical literature on jobs adds has concluded that low-carbon jobs require more skills than equivalent high-carbon ones (Vona et al., 2015; Saussay et al., 2022; Consoli et al., 2016). I adopt a different approach and use my frameworkt to answer that question at the industry level: is emission-saving technical-change labour-biased? And whether the answer is yes or now: is the effect the same on all levels of skills?

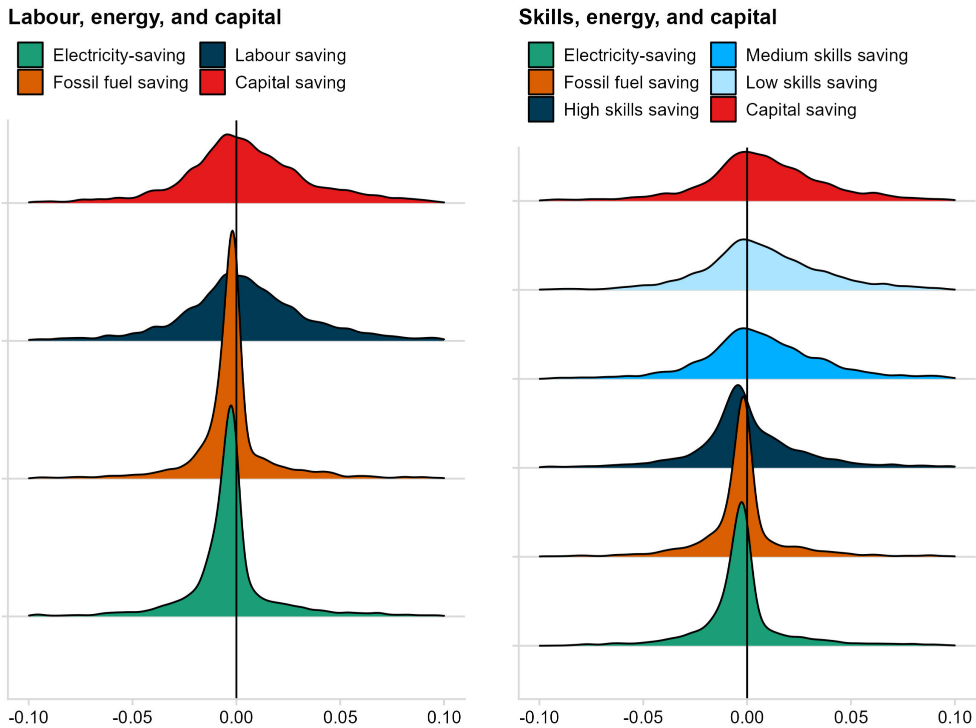
This issue of skills and emissions is typically an issue that requires multiple inputs for which my framework is most adapted. I need to consider at least skilled vs unskilled labour and emissions. In this section I consider two frameworks with i) capital, labour, electricity and fossil fuel, and ii) capital, low skills labour, medium skills, high skills labour, electricity and fossil fuel.

In this section, I first present some facts about the energy-saving trends, cross industries and countries. I then explore the correlation between the different direction of technical change to answer my question. Note that for data availability reasons, most of the analysis is focused between 2010 and 2019, therefore before the start of any serious energy transition efforts.

6.1 Energy-saving trends

Figure 11 shows the distribution of the factor-saving technical change. Capital and labour-saving technical change distributions are widespread and centered around zero, there is no obvious bias. Interestingly, the disaggregated labour date (right panel) shows a left-skewed distribution of high-skills labour-saving technical change, meaning for most industries and countries, technical change is actually high-skills labour-using. Likewise, technical change exhibit electricity-using and fossil-fuel using. Note that the fact that capital and energy technical change intensities are similar in both framework is not a coincidence. The framework is robust to adding more inputs or disaggregating them. The λs values and fluctuations for capital, electricity and fossil fuel are mostly similar in the two frameworks. See appendix E for more details.

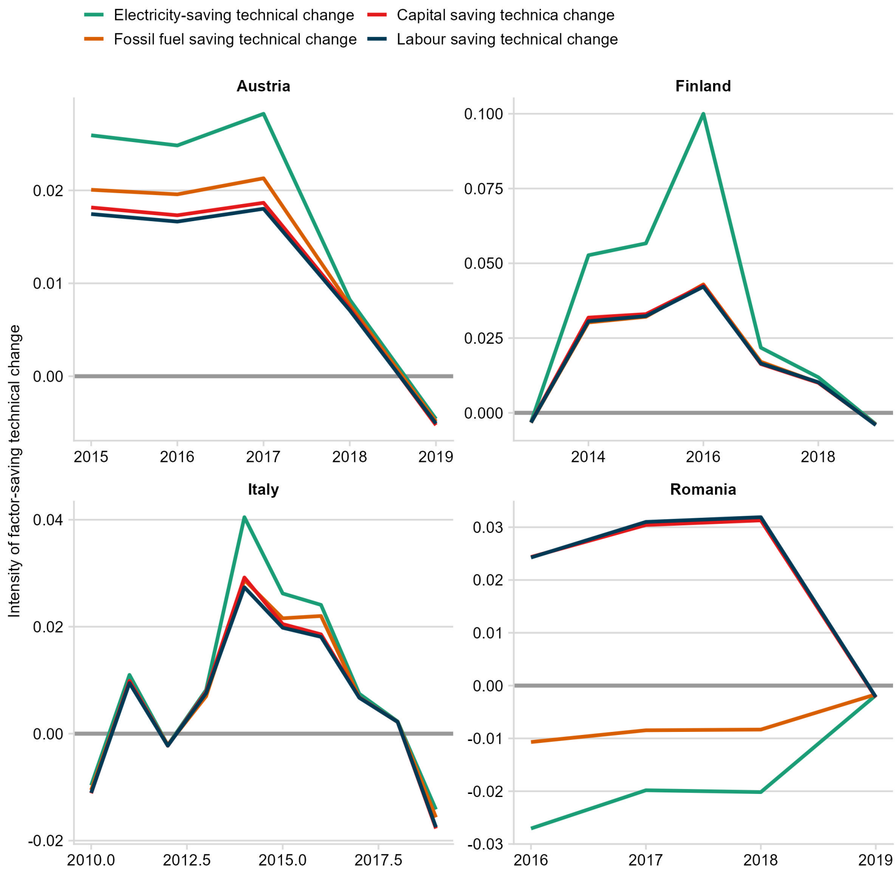
Figure 11: Distribution of the intensities of technical change for two frameworks with aggregated and disaggregated labour.



Note: A positive value of the "factor-saving" technical change means that the country manufacturing sector is saving on this input, while a negative value indicate a factor-using technical change. A distribution being skewed to the right means that most of the technical change for this factor is factor-saving. I have normalised the intensities of technical change (λs) by the factor share to have comparable metrics.

The values of the bias of technical change gives expected results: richer economies are saving on most inputs, while lower income countries are energy-using. Figure 12 shows the technical change bias in four manufacturing sectors. Italy, Finland and and Austria exhibit mostly factor-saving technical change with little bias as the λs value are somewhat close. Unlike Romania, which exhibit a clear energy-using bias and labour- and capital-saving bias. It checks out with the development of the country, where automation and mechanisation in the manufacturing industries took place after Romania joined the EU in 2007 and benefiting from massive European subsidies.

Figure 12: Factor-saving technical change for Austria, Finland, Italy, Romania manufacturing sectors



Note: A positive value of the "factor-saving" technical change means that the country manufacturing sector is saving on this input, while a negative value indicate a factor-using technical change. Finland saves on all input whereas Romania saves on labour and capital but is both electricity-using and fossil fuel-saving.

When splitting the distribution of technical change intensities per sector, it ,appears clearly that "heavy" sectors, including manufacturing, agriculture, transport and energy sectors, have a wider distribution indicating that more technical change takes place in these sectors that in services (e.g. Education, real estate) that exhibit narrower distributions (see figure F.18 in appendix F). Mining shows a clear trend in energy-saving and labour-saving constrated by a wide distribution of capital-saving λ both positive and negative (indicating that both capital-using and capital-saving technical change take place). Services unsurprisingly show capital-saving, labour-saving and energy-using technical change.

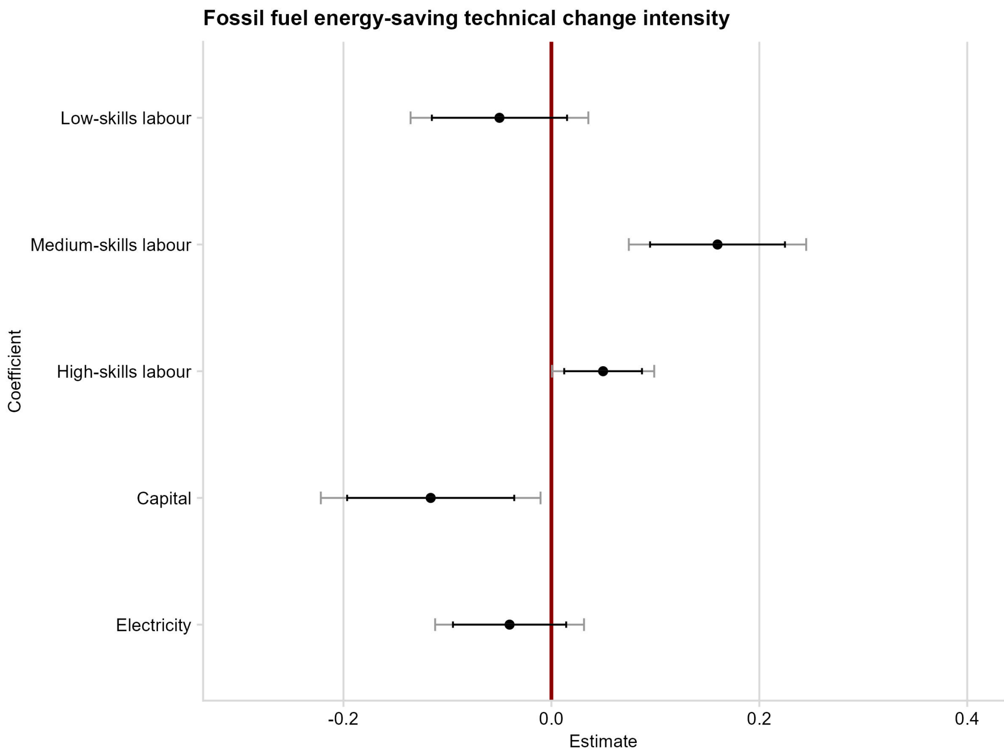
The split per country is also full of information, higher income countries (France, Germany, Austria) have narrower distribution of intensities, mostly saving on all inputs. Lower income countries such as Latvia, Romania, Slovakia, Hungary and Slovenia show greater intensities of technical change, with a clear distinction between right-skewed distributions for fossil fuel, electricity and high skills (fossil-fuel using and electricity-using) while being very much capital-saving, low-skills saving and medium-skills saving.

6.2 Skill-bias of fossil-fuel saving technical change

The quality of the data I have does not allow me a true causality inference. However, exploring the correlations between the directions of technical change is rich. Figure 13 shows that there are significant and positive relationships between fossil fuel-saving technical change (in first difference) and medium/high-skills labour-saving. On the contrary, there is a negative correlation with capital-saving technical change (see also Table F.8 in Appendix F.B). This result is robust to a number of specification (see Table F.8) and to restriction in data to allow for longer time series only. The fixed effects coefficients for industry and sector are never significant. Different specifications bring also a negative relationship between fossil fuel-saving and electricity-saving technical changes. This is expected and means that innovation or new processes allowing to reduce emissions are electricity-using or are complemented by electricity-using technology.

This result is key: green technical change, meaning fossil-fuel saving (emission saving) technical change also saves on skilled labour (high skills and medium skills). Within a simple demand and supply framework for labour as in Goldin and Katz (2007), this result could mean that green technical change, by reducing demand for skilled labour, would decrease the skills wage-premium. This result seems to contradict Vona et al. (2015); Saussay et al. (2022); Consoli et al. (2016) who find that skilled-labour increased with the net zero transition. Two main arguments could explain such a result: i) low-income countries such as Romania or Latvia are well represented in my sample, unlike the studies I cited focusing on high-income countries, ii) these studies focus on green jobs, but here fossil-fuel saving technical change can arise in all sectors, even and maybe especially in carbon-intensive industries.

Figure 13: Correlation of fossil fuel saving with other factor-saving technical change



Note: Regression of $\Delta\lambda_{\text{fossil}} \sim \Delta\lambda_{\text{LS}} + \Delta\lambda_{\text{MS}} + \Delta\lambda_{\text{HS}} + \Delta\lambda_{\text{K}} + \Delta\lambda_{\text{elec}} + I_{\text{country}} + I_{\text{sector}}$. 1Y data. Long series only (n>=8), Lambdas normalised by their alpha. First interval is 95%, second is 99%. Trim valued (within [-1,1]).

7 New insights on Hicks's hypothesis

7.1 Definitions & Specifications

In this paper I 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, I 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.[25]

I translate Hicks' hypothesis using the relative direction of technical change and the evolution of prices:

$$\frac{\lambda_L}{\lambda_K} \sim \Delta w + \Delta r \Longleftrightarrow \frac{\lambda_L}{\lambda_K} = a_w^{L/K} \Delta w + a_r^{L/K} \Delta r + \varepsilon, \tag{18}$$

with $a_r^{L/K}$ and $a_w^{L/K}$ the estimated coefficients. Appendix G..1 provides alternatives specifications for this hypothesis and discuss their validity.

7.2 Empirical strategy

To test Hicks's hypothesis, I am using the relative intensity of technical change on the evolution of prices. Nevertheless, two issues emerge. The first is the intrinsic bias of the framework since λs are computed using factor price. The second is the potential endogeneity through a feedback effect of prices on technical change. I address these two issues in this section.

In a nutshell, I instrument factor prices at the industry level with national price fluctuations. It allows me to capture only the direct effect of prices on technical change in each sector and 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.

7.2.1 Intrinsic bias of the framework

Intrinsic bias issue The theoretical framework that I have developed is biased against the Hicks's hypothesis. If I regress the equations of the previous section, I will only reflect a mechanical influence of prices on the intensities of technical change λs through the factor shares that I use to compute the λs.

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. Appendix G.A further explore this issue and state using the framework notations.

I offer an empirical strategy to overcome this bias in the next paragraph 7.2.

Solution: random data generation process To quantify the intrinsic bias of the framework, I generate 20,000 randomly generated time series. Testing the Hicks' hypothesis on these data will reveal the underlying mechanisms. Comparing the results obtained from the real data with the results obtained from these data will make it possible to separate the real effect from the mechanism described.

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. I compute the output as $Y = rK + wL$. I 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. I ensure ex-post that the factor shares follow a normal distribution.

[25]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.

7.2.2 Endogeneity

Feedback loop 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.

Instrumentation 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.

I 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. I 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 optimal, 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 C.7).

I use standard two-stage least-squares estimation (2SLS). I 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. I test adding lagged national prices as instruments in the first step. Given the diversity of the industries I estimate for, I consider this search of the best instrumentation for each sector does not bias the results. The results I present still hold if I limit myself to the same specification and instrumentations for all sectors on all four databases.[27] Some first steps regression tables are available in Appendix G.I.

Data & Method I use the four datasets presented in section 4. 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 I also correct the time trend of the price series and obtain stationary series. The λs series are naturally stationary.[29]

Prior to the estimation, I check each series for potential outliers. To that end, I 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.

[26] In the case of the U.S., I 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, I 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.

[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.

I consider only the estimates whose instrumentation is strong (F-statistics), consistent (Wu-Hausman test) and valid (Sargan overidentification test). I 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 me to test the null hypothesis that the OLS is at least as consistent as the IV. I keep only the estimates rejecting H_0 at the 5% threshold. The Sargan test tests the hypothesis that all the instruments are compatible. I do not include the industries rejecting this hypothesis at the 5% threshold. First steps estimates are available in Appendix G.I.

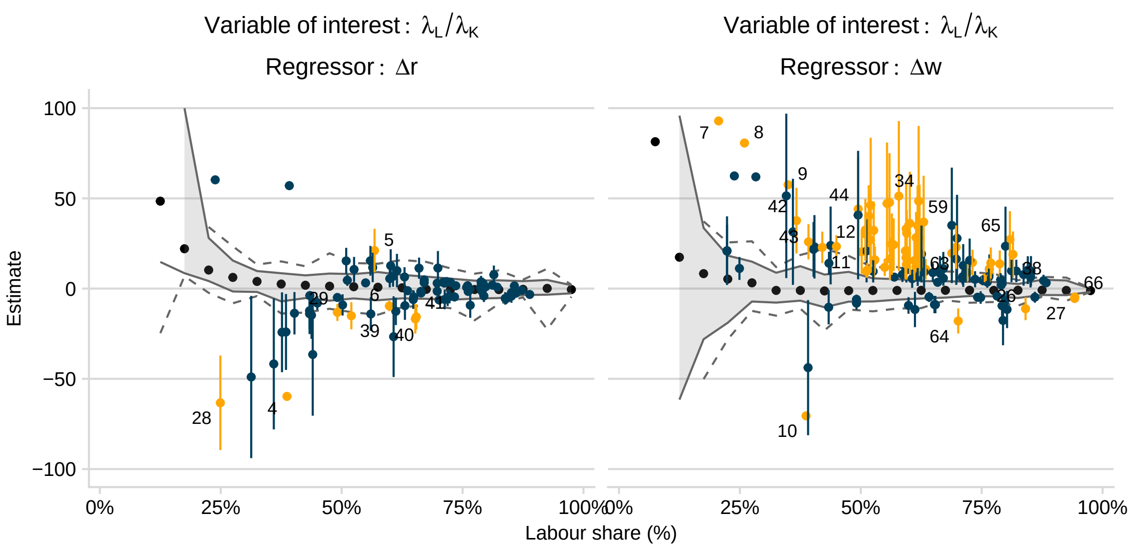
7.3 Price variations on relative technical change

Estimated equation I estimate the coefficients $a_r^{L/K}$ and $a_w^{L/K}$ of equation (27), that I 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 G.9 (Appendix G.B). 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.

Figure 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 (27) 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 G.10.
Data: KLEMS US (1986-2019), KLEMS EU+ v2021 (1997-2019), KLEMS EU+ v2017 (1997-2015), KLEMS EU+ v2008 (1970-2005)

Results Figure 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]

I 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 14). On the contrary, λ_L/λ_K estimates are significantly negatively correlated with an increase in capital price.

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. I 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 G.10, in appendix G.B).

7.4 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. I 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.

I 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 me to eliminate the feedback effect of technical change, which would tend to moderate price changes. The second step compares my 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 I am 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 me to conclude that some induced innovation effects are taking place.

In more detail, I find several effects in line with Hicks's hypothesis (I indicate when the observed effect is sparse and thus less reliable than other results). I 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. I also find that capital-using technical change increases with labour price; and labour-using technical change increases with capital price (sparse). I 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, I 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).

[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 I have chosen to retain the more demanding criterion. Considering both intervals at 95% gives similar results for a smaller number of sectors.

I 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. I highlight a large heterogeneity in the responses to price increases across industries

The industries and countries represented are sufficiently varied to ensure that my results are not due to a single systematic bias. The data I handle are subject to many biases and measurement errors, for example the valuation of capital service flows. I have used different databases with different levels of detail and methodologies, so I have introduced additional noise. Under these conditions, the effects I obtain are remarkably clear and show price-induced technical change.

8 Forecasting factor shares

In this section, I forecast the labour share dynamics in each industry. One of the major contributions of this paper 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.

my forecast of the labour share serves two purposes: to offer another practical application of my framework and to check the validity of my framework by comparing it to a selection of other production functions: CES, Leontief and Cobb-Douglas.

An advantage of my 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 my framework does not rely on the estimation of one single elasticity of substitution between capital and labour.

The principle is to split the data set between a training set of data and a testing set where I use the previously calibrated model to forecast factor share assuming perfect knowledge of the prices of labour, output and capital. I use a standard split of 80%/20% between the training and the testing set.[33] That is, out of 33 years available, I use the data 1987-2012 for the training set, and leave 2013-2019 for the testing set.

The input of the forecast is the time series of factor prices. The output is the factor share. For the training set, all observations are used: quantities, prices and factor shares.

I train my framework in two steps. First, I notice an empirical regularity between the intensity of technical change (λs) and the allocation of inputs to the production function (βs). I then regress the βs on the λs. To compute λs, I only need past quantities and current prices. I can then compute the βs based on the estimated relationship. From βs and λs I can compute the labour and price quantities, and factor share at the current time. Which will then be used to compute the next λs. To estimate the CES, I follow Klump and de La Grandville (2000), Temple (2012) and Young (2013). Details are available in appendix H.B.

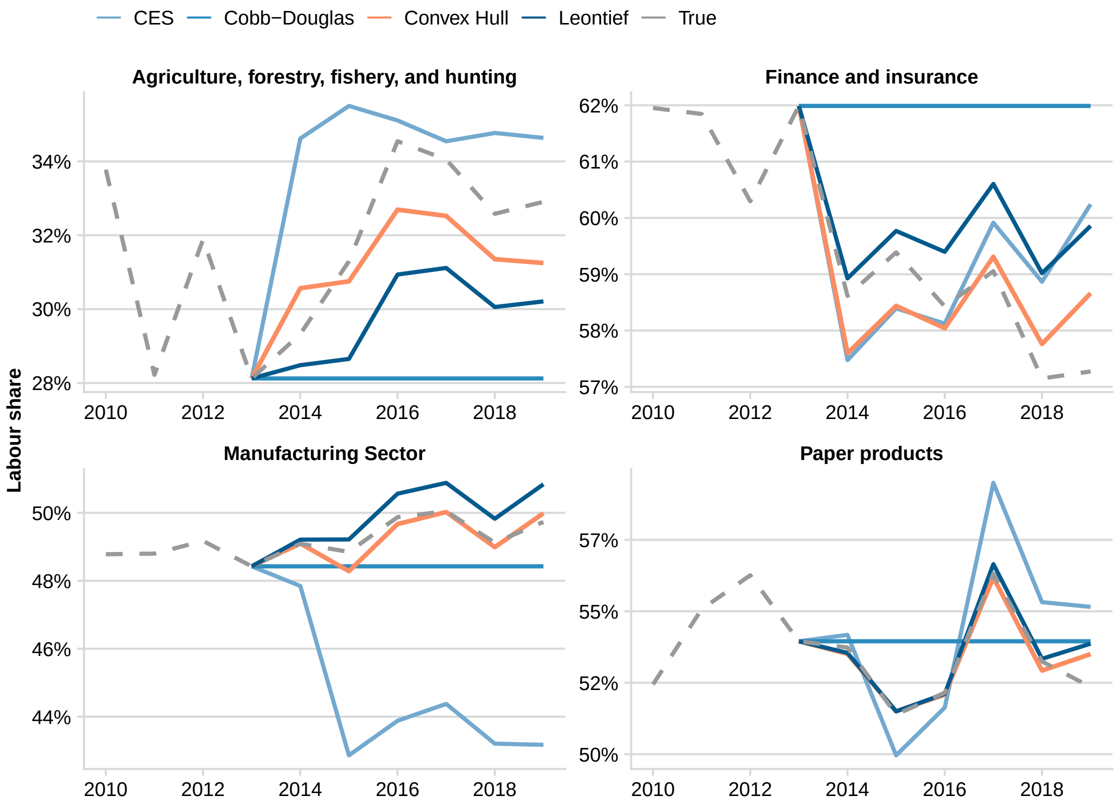
8.1 Testing set — Comparing forecast

I 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). I compare the forecast of the share of labour until 2019 to the true value. I use root-mean-squared percentage error (RMSPE) to choose the best forecast.[34] For each of the four models I retain the best specification in terms of error.

[33] This assumption is relaxed in the course of the analysis.

[34] I 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.

Figure 15: Forecast of labour share using my framework vs the true value (grey) and the 3 other models



Note: For each model I retain the specification allowing the forecast with the lowest error (RMSE).

Figure 15 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 my framework, but I should humbly note that the Leontief model also performs very well. My framework is able to anticipate shocks to the labour share. These shocks are most likely price-related, since Leontief functions and my 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 my model is closer in level to the actual labour share than the Leontief model.

The specification chosen for my framework allows me to accurately anticipate variations in the labour share by reproducing the technical change bias (λ_L/λ_K) (see in appendix, figure H.36).

Table 4 shows the percentage of sectors (unweighted) for which each model provides the best forecast over the 2013-2019 period. My framework "convex envelop" receives the highest score compared to the other three models. I compare the forecast performance of models 1 against 1. My model is the only one that performs better than any other model.

Table 4: Comparing the four models predictive power

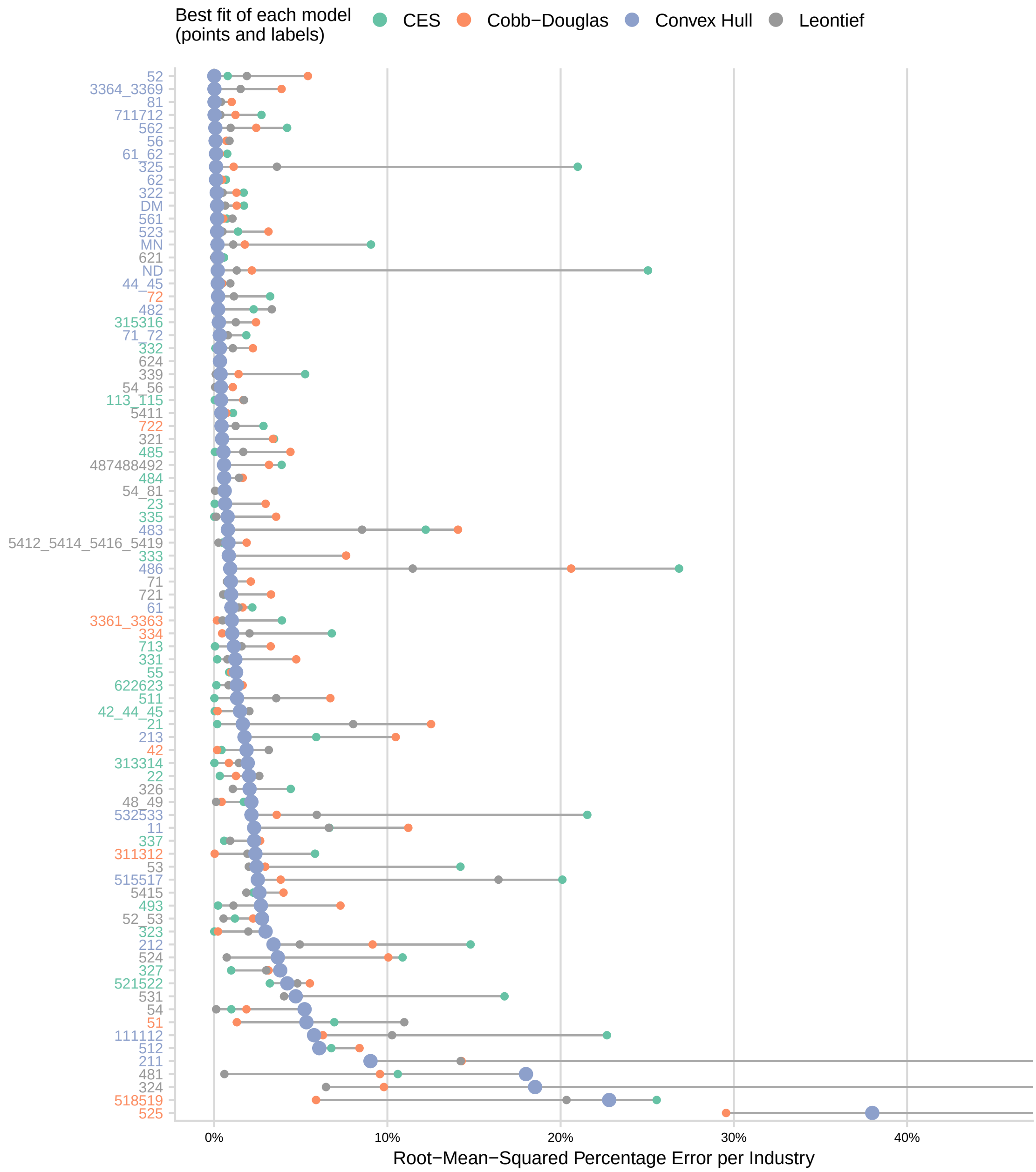
	CES	Cobb-Douglas	Convex envelop	Leontief
Comparing the four models predictive power				
Best model	26%	11%	36%	27%
Comparing one model predictive power (line) to another (row)				
CES	100%	53%	63%	63%
Cobb-Douglas	47%	100%	72%	70%
Convex envelop	37%	28%	100%	43%
Leontief	37%	30%	57%	100%

I compare the performance of the 4 models across all sectors and present the results in figure 16. The colours of the sector codes on the vertical axis indicate which is the best model. They reflect the numbers of Table 4. First result: in the cases where my 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. My framework offers a very poor forecast for 6 sectors located at the bottom of the graph with an error higher than 5% on average.[35] For 4 of them, the other models also have an average error of 5%, and for two of these models, as bad as my forecast is, it is nevertheless the best in the basket of models. There are a few industries where my framework performs significantly better than the competing models.[36] In summary, the predictive power of my framework consistently provides a labour share forecast that is at least as good as all other models pooled together.

[35] 512, 211, 481, 324, 518519, 525, see appendix, table C.1.

[36] 325,ND,483,486.

Figure 16: 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 C.1, for the industries nomenclature. My model is denoted "Convex Hull".

I 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 my rough method of estimating substitution elasticities does not disadvantage the CES functions, I report the results including only the sectors for which Young (2013) estimates a substitution elasticity in figure H.35.[37] The results are very similar and the performance of CES remains erratic.

[37] It does not ensure that it is his elasticity that I use, I retain the best CES specification for this sector.

8.2 Sensitivity analysis: testing set size and starting year of the forecast

I test the sensitivity of my 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). I have varied the start of the training period from 2010 — meaning that the training set is now 70% of the dataset — to 2018, where I try and forecast only the next year labour share.

In a nutshell, my framework performs significantly better than CES on longer periods. 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. The longer the forecasting period, the greater the gap between the models. For details, see appendix H.D.

8.3 Policy Impact & Summary

I have shown that my framework ("Convex envelop") allows me to accurately forecast the evolution of the factor shares of almost all 81 sectors of the KLEMS US database. In all cases, my framework is better or as good as the other competing models (CES, Cobb-Douglas and Leontief). My model is validated by its predictive power. The simplicity of the forecast process of my 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 my framework provides an understanding and prioritisation of the processes at work.

I could try to make longer term predictions with my model, but this is perilous exercise. A preliminary attempt is in appendix H.E.

9 Conclusion

In this paper, I have exposed a framework disentangling the directions of technical change and factor substitution. I start by reminding the limitations of the CES functions to represent the bias of technical change at the industry-level and multiple inputs. I then recall a paper by Atkinson and Stiglitz (1969) and their "new view of technological change" as localised and biased. Building on that framework, I describe technical change as an increase in the technology with purely factor-saving distortion of an initial Leontief production function. The new function is the convex envelop of the combination of these technologies. It is piecewise linear and allows for substitution. This framework is compatible with the tasks-based model of directed technical change (Acemoglu, 2015) and a global production function being CES (Jones, 2005).

This framework allow me 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.

I have performed a number of analyses with the framework described. I compute the technical change indicators on the KLEMS database for the U.S., European countries and some other OECD countries.

First, I 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. I can relate the trends in the direction of technical change to new technologies or specific national events. This makes my framework a prime tool for studying and comparing the dynamics of technical change in different countries and industries. I have proven that my framework can accurately describe known factor-saving technologies (e.g. more efficient digital printers in the printing industry) and provide consistent estimate of the bias, unlike a CES production function. This proof of concept shows the robustness and utility of this framework.

Second, and this is the main result of the paper, I show that fossil fuel saving technical change is correlated in first differences with skilled-labour saving technical change and electricity-using technical change but not with unskilled-labour saving technical change. It might indicate that green technical change and emissions reduction could potentially decrease the skills wage gap premium.

Third, I show 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 I 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.

Fourth, my framework is able to accurately forecast the dynamics of labour and capital shares in value-added. I 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 my framework and opens new research avenues on the evolution of technical change in the short term using this framework.

Despite the strong hypothesis of using Leontief production functions, the growth and technical change accounting framework developed in this paper 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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A Proof of Lemmas

Proof of Lemma 1

Proof. F and F' are two Leontief production functions:

$$\begin{array}{rlcl} F: & \mathbb{R}_+ \times \mathbb{R}_+ & \to & \mathbb{R}_+ \\ & (K,L) & \mapsto & F(K,L) = Y = Y_0 \cdot \min\left(\frac{K}{K_0}, \frac{L}{L_0}\right) \end{array}$$

with $Y_0 = F(K_0, L_0)$.

We can write the intensive production function associated with F:

$$\begin{array}{rlcl} f: & \mathbb{R}_+ & \to & \mathbb{R}_+ \\ & k & \mapsto & f(k) = y = y_0 \cdot \min\left(\frac{k}{k_0}, 1\right) \end{array}$$

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 optimal ratio of the function F.

$$\begin{array}{rlcl} F': & \mathbb{R}_+ \times \mathbb{R}_+ & \to & \mathbb{R}_+ \\ & (K,L) & \mapsto & F'(K,L) = Y = Y_0' \cdot \min\left(\frac{K}{K_0'}, \frac{L}{L_0'}\right) \end{array}$$

that we can write intensively

$$\begin{array}{rlcl} f': & \mathbb{R}_+ & \to & \mathbb{R}_+ \\ & k & \mapsto & f'(k) = y = y_0' \cdot \min\left(\frac{k}{k_0'}, 1\right) \end{array}$$

with $k_0' = K_0'/L_0'$ and $y_0' = Y_0'/L_0'$.

A line in $\mathbb{R}^2$ is a set $\left\{(x,y) \in \mathbb{R}_+^2 | ax + by + c = 0, (a,b) \neq 0, (a,c,b) \in \mathbb{R}^3\right\}$. 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 me 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 me 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.

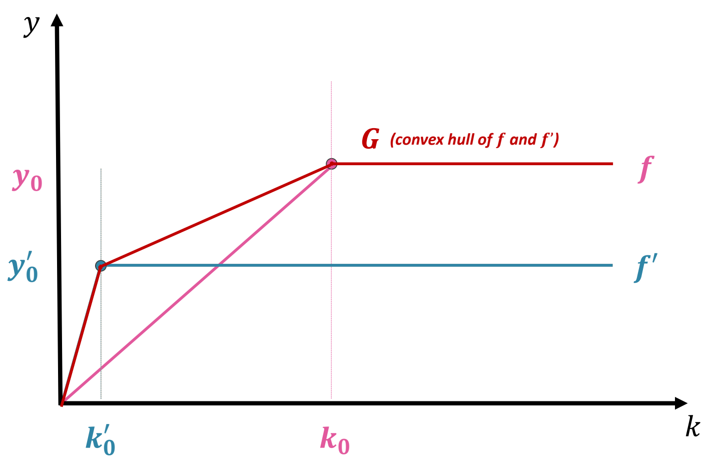
2. If there is an intersection point at (k^*, y^*) such that $k^* \in]0, k_0'[$ and $f(k^*) = f'(k) = y^*$. Since $k/k_0 < k/k_0' < 1$, then $f(k^*) = y_0 \cdot \min\left(\frac{k^*}{k_0}, 1\right) = \frac{y_0 k^*}{k_0} = \frac{y_0' k^*}{k_0'}$. Since $k^* > 0$, hence $\frac{y_0}{k_0} = \frac{y_0'}{k_0'}$. $\forall k > 0, f(k) = y_0 \cdot \min(k/k_0, 1) = \frac{y_0}{k_0} \cdot \min(k, k_0) = \frac{y_0'}{k_0'} \cdot \min(k, k_0) \geq \frac{y_0'}{k_0'} \cdot \min(k, k_0') = f'(k)$ 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

Figure A.1: Illustration intensive framework Lemma 2



Proof. **1. Maximum production function**

Let us have two non-dominated Leontief functions, F and F', defined by their optimal 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 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' optimal ratios, it is optimal to use only one of the two local production functions, then that between their optimal ratios it is optimal to allocate some inputs to both production functions.

If $\bar{k} < k_0'$ $\quad\forall \bar{K}, \bar{L} > 0,\ \alpha, \beta > 0,$

$$
\begin{aligned}
&F'(\bar{K},\bar{L}) - F'(\alpha\bar{K},\beta\bar{L}) - F((1-\alpha)\bar{K},(1-\beta)\bar{L}) \\
&= y_0'\bar{L}\min\left(\frac{\bar{k}}{k_0'},1\right) - y_0'\bar{L}\min\left(\frac{\alpha\bar{k}}{k_0'},\beta\right) - y_0\bar{L}\min\left(\frac{(1-\alpha\bar{k})}{k_0},1-\beta\right) \\
&= y_0'\bar{L}\frac{\bar{k}}{k_0'} - y_0'\bar{L}\min\left(\frac{\alpha\bar{k}}{k_0'},\beta\right) - y_0\bar{L}\min\left(\frac{(1-\alpha\bar{k})}{k_0},1-\beta\right) \\
&\geq y_0'\bar{L}\frac{\bar{k}}{k_0'} - y_0'\bar{L}\frac{\alpha\bar{k}}{k_0'} - y_0\bar{L}\frac{(1-\alpha\bar{k})}{k_0} \\
&= \bar{L}(1-\alpha)\left(\frac{y_0'}{k_0'} - \frac{y_0}{k_0}\right) \\
&\geq 0\,.
\end{aligned}
\tag{19}
$$

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 $y_0 > y_0'$

$$
\begin{aligned}
&F(\bar{K},\bar{L}) - F'(\alpha\bar{K},\beta\bar{L}) - F((1-\alpha)\bar{K},(1-\beta)\bar{L}) \\
&= y_0\bar{L} - y_0'\bar{L}\min\left(\frac{\alpha\bar{k}}{k_0'},\beta\right) - y_0\bar{L}\min\left(\frac{(1-\alpha\bar{k})}{k_0},1-\beta\right) \\
&\geq y_0\bar{L} - y_0'\bar{L}\beta - y_0\bar{L}(1-\beta) \\
&= \bar{L}\beta\left(y_0 - y_0'\right) \\
&\geq 0\,.
\end{aligned}
\tag{20}
$$

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:

$$
\begin{aligned}
G(K,K',L,L') &= Y_0\min\left(\frac{K}{K_0},\frac{L}{L_0}\right) + Y_0'\min\left(\frac{K'}{K_0'},\frac{L'}{L_0'}\right) \\
&= y_0 L\min\left(\frac{k}{k_0},1\right) + y_0'L'\min\left(\frac{k'}{k_0'},1\right) \\
&\leq y_0 L + y_0'L'\,.
\end{aligned}
\tag{21}
$$

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

$$
\begin{cases}
L = \bar{L}\dfrac{\bar{k} - k_0'}{k_0 - k_0'} \\
L' = \bar{L}\dfrac{k_0 - \bar{k}}{k_0 - k_0'} \\
K = k_0 L = \bar{L}\dfrac{k_0(\bar{k} - k_0')}{k_0 - k_0'} \\
K' = k_0' L' = \bar{L}\dfrac{k_0(k_0 - \bar{k})}{k_0 - k_0'}
\end{cases}
\,.
\tag{22}
$$

which check that $K/L = k_0$ and $K'/L' = k_0'$.

Hence, from (22):

$$
G^*(\bar{K},\bar{L}) = \bar{L}\left(y_0'\frac{k_0 - \bar{k}}{k_0 - k_0'} + y_0\frac{\bar{k} - k_0'}{k_0 - k_0'}\right)\,.
\tag{23}
$$

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 $(\bar{K}, \bar{L})$, $\forall \bar{K}, \bar{L} > 0$,

$$\begin{aligned}
&F(\bar{K},\bar{L}) - F'(K',L') - F(K,L) \\
&= y_0 \bar{L} \min\left(\frac{\bar{k}}{k_0}, 1\right) - y'_0 \bar{L} \frac{k_0 - \bar{k}}{k_0 - k'_0} \min\left(\frac{k'}{k'_0}, 1\right) - y_0 \bar{L} \frac{\bar{k} - k'_0}{k_0 - k'_0} \min\left(\frac{k}{k_0}, 1\right) \\
&= y_0 \bar{L} \frac{\bar{k}}{k_0} - y'_0 \bar{L} \frac{k_0 - \bar{k}}{k_0 - k'_0} - y_0 \bar{L} \frac{\bar{k} - k'_0}{k_0 - k'_0} \\
&= \bar{L} \frac{k_0 - \bar{k}}{k_0 - k'_0} \left(\frac{y_0}{k_0} k'_0 - y'_0\right) \\
&< 0\,.
\end{aligned} \tag{24}$$

Likewise,

$$\begin{aligned}
&F'(\bar{K},\bar{L}) - F'(K',L') - F(K,L) \\
&= y'_0 \bar{L} - y'_0 \bar{L} \frac{k_0 - \bar{k}}{k_0 - k'_0} - y_0 \bar{L} \frac{\bar{k} - k'_0}{k_0 - k'_0} \\
&= \bar{L} \frac{\bar{k} - k'_0}{k_0 - k'_0} (y'_0 - y_0) \\
&< 0\,.
\end{aligned} \tag{25}$$

It proves that for $\bar{k} \in [k'_0, k_0]$, my assumption of a non-zero combination of the two functions F and F' was right. We also get that the allocation given in equation (22) reaches the maximum output $y_0 L + y'_0 L'$, thus no other combination can provide a higher output given the constraint on inputs.

The global production function G is the convex envelop 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

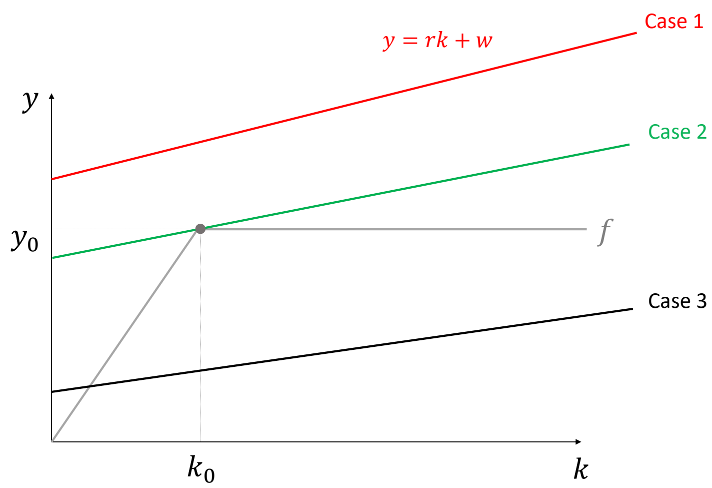
A market equilibrium assumes the existence of a uniquely determined price vector balancing supply and demand. That is typically not possible with Leontief functions, since such a function is not differentiable at its efficient use (at its optimal ratio k_0).

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 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 $rk_0 + w < y_0$.

Figure A.2: One-Leontief intensive setting



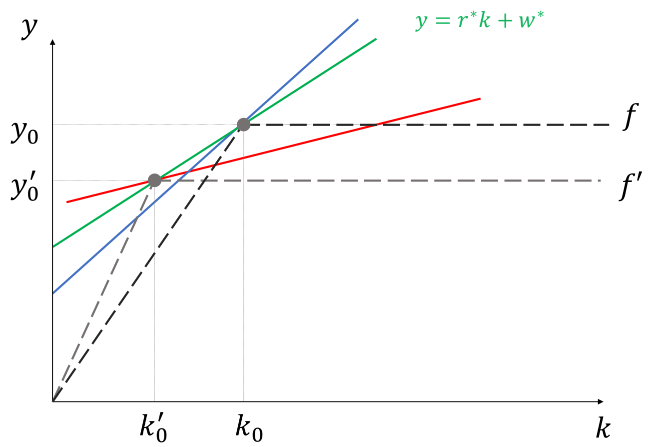
There cannot be more than two intersections points, because if there were then the demand curve would be flat, meaning a zero capital cost. It is neither possible to have the single intersection point at the origin, since it would correspond to a zero wage rate.

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 optimal 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.

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 my situation, we consider a two-Leontief setting, with f and f' as represented in Figure 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 optimal ratios of the two functions. The equilibrium price vector (k^*, w^*) is then defined unambiguously.

Figure A.3: Two-Leontief intensive setting



[h]

□

B Theoretical framework

B.A Framework applied to labour or capital-using situations

In this section we show patterns similar to Figure 5 but with one or two $\lambda < 0$, i.e. a technical change labour or capital using. The figures B.4 and B.5 feature positive βs.

The figure 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 B.4: Illustration of a case capital and labour-using with capital deepening and widening

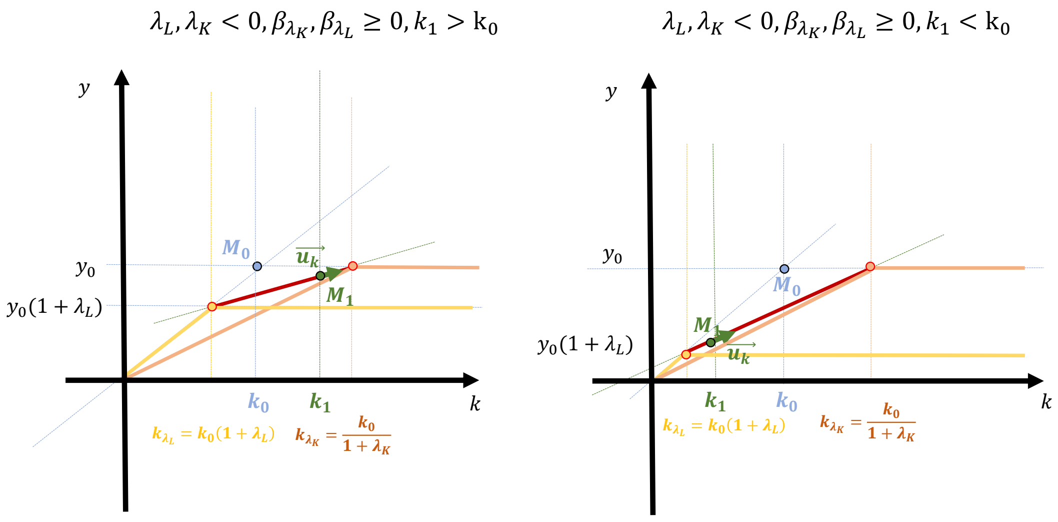


Figure B.5: Illustration of a case of capital-using and labour-saving with capital deepening and widening

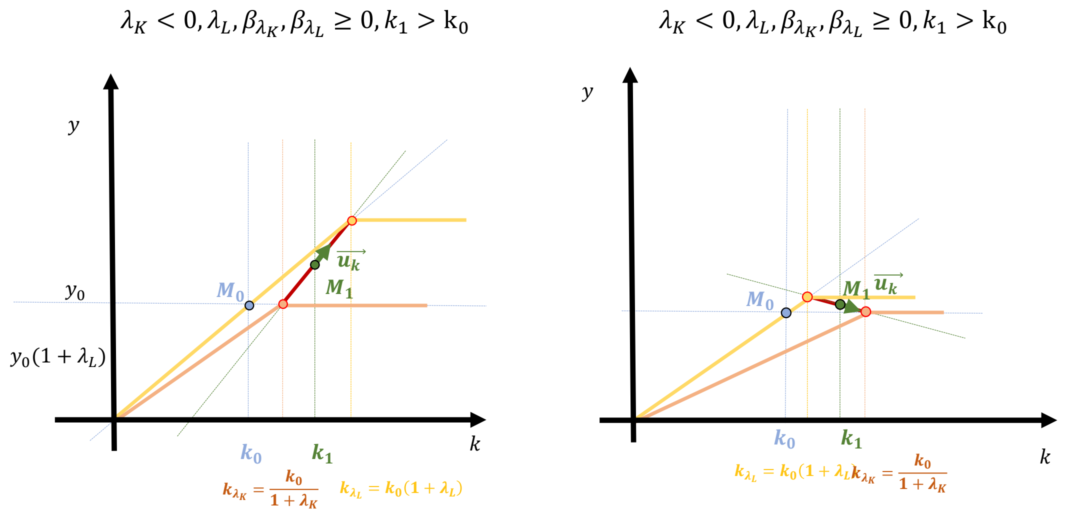
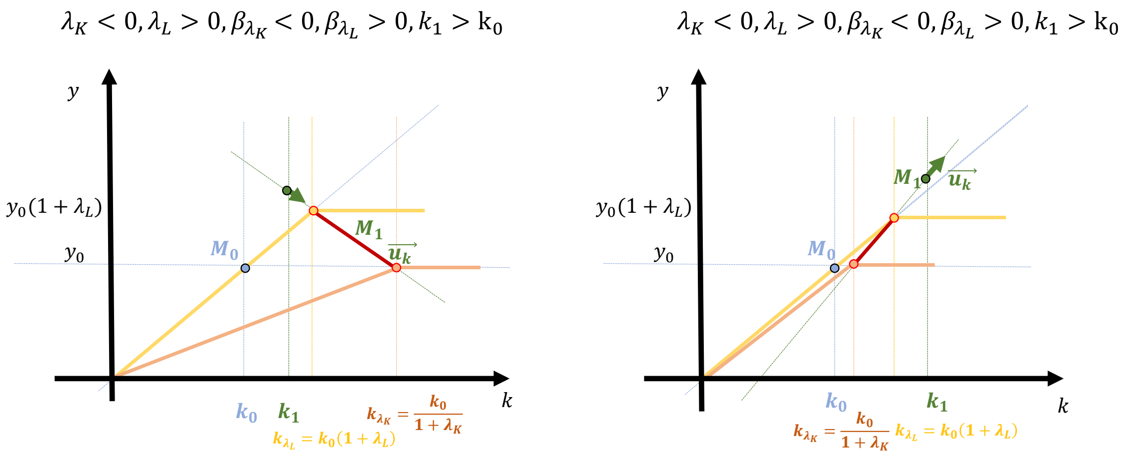


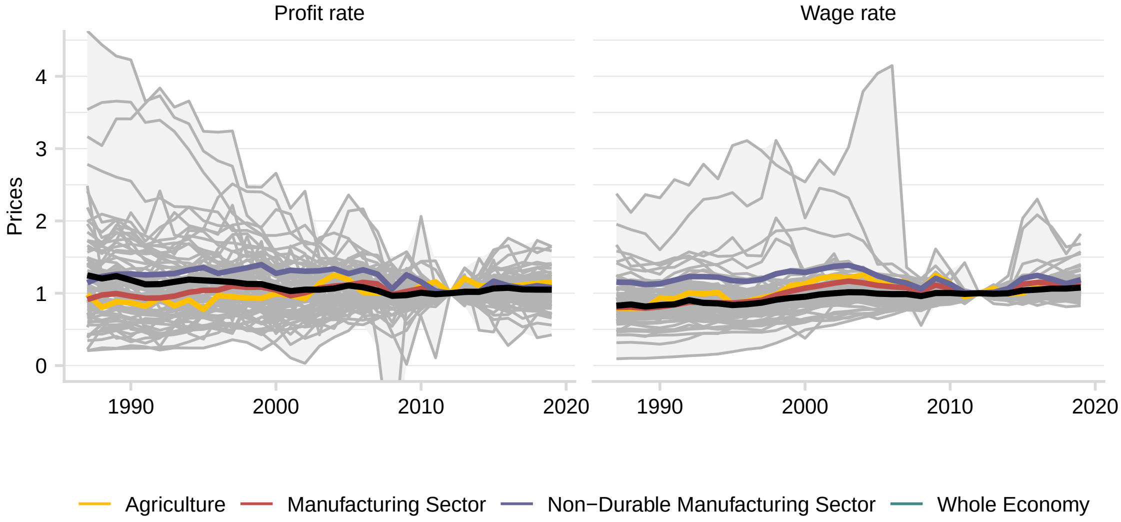
Figure B.6: Illustration of a case of capital- using and labour-saving with capital deepening and widening (with negative use of the K-saving function)



C Description of U.S. factor-saving technical change

C.A Prices of all 81 US industries

Figure C.7: Prices for all 81 U.S. industries



Note: Prices normalised to 1 in 2015. Macro prices are aggregated using gross output data.

C.B KLEMS US NAICS nomenclature

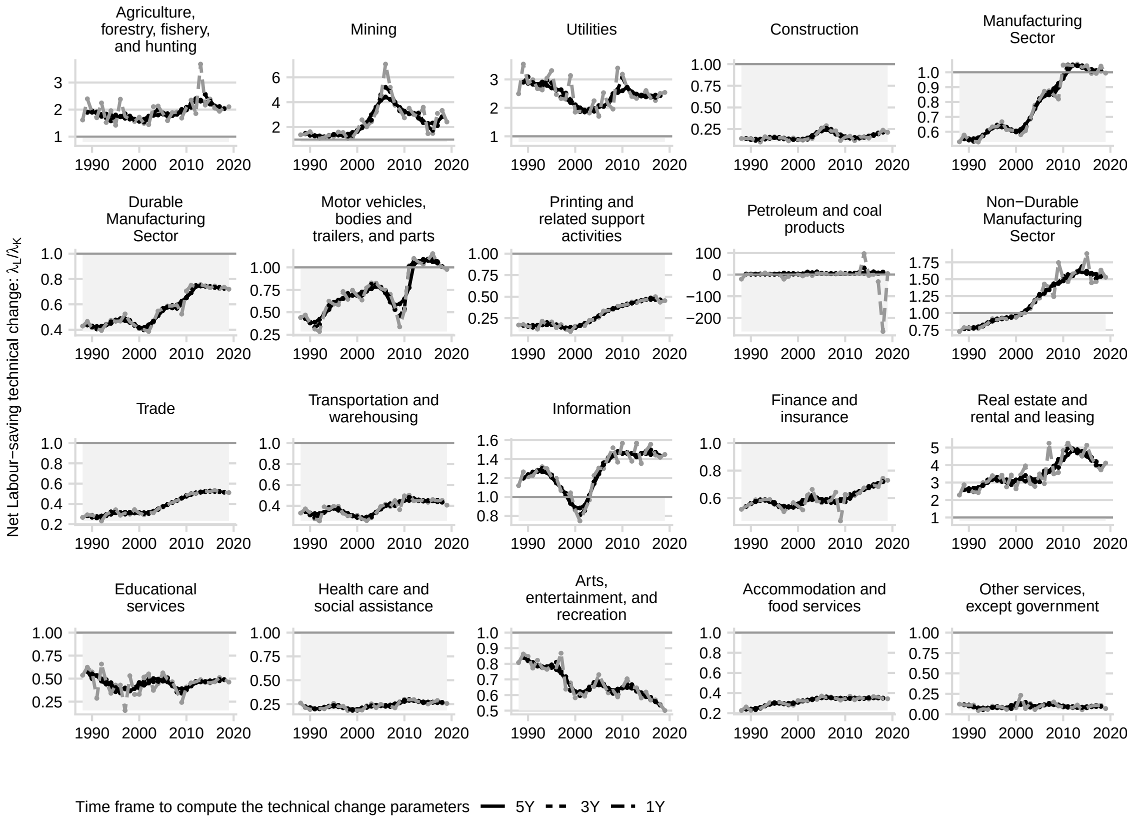
Table C.1: NAICS industry - KLEMS US database

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

C.C U.S. sectoral net labour-saving technical change

Figure C.8 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 5, Figure 8). 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.

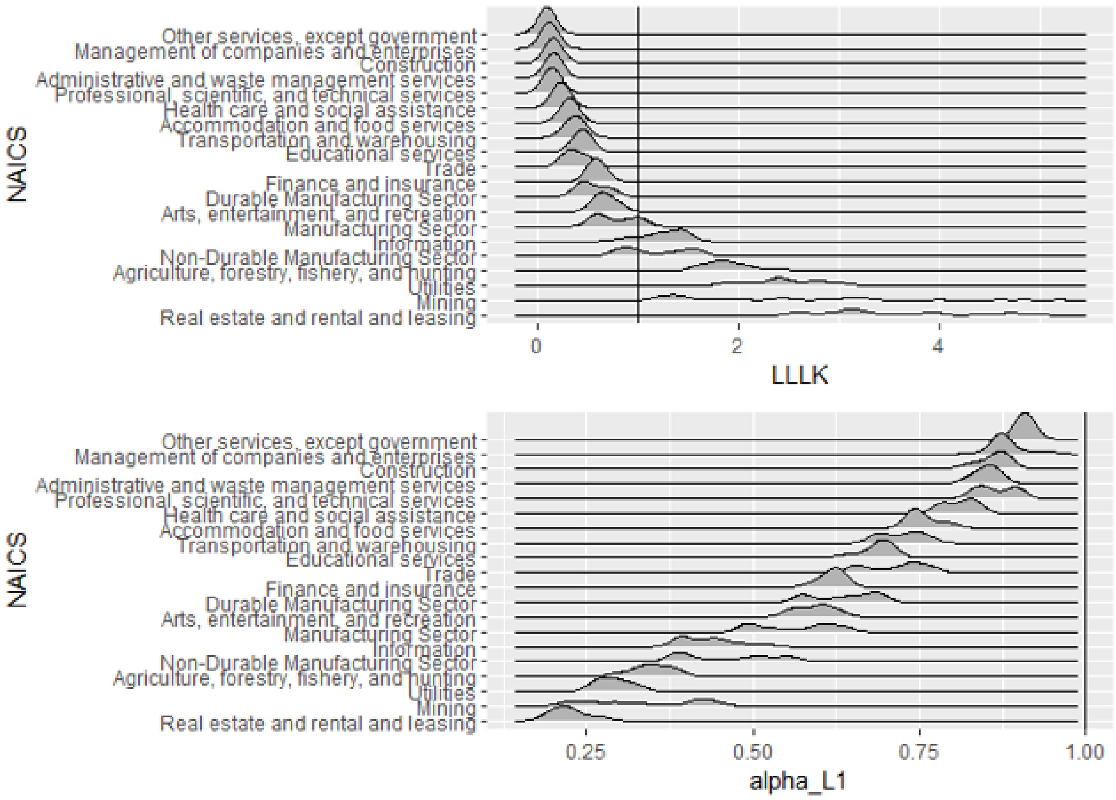
Figure C.8: Net Labour-saving technical change (λ_L/λ_K) in U.S. industries



C.D 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 C.9).

Figure C.9: 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

C.E 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 5: Printing sector (Figure C.2), Agriculture (C.3), Information (C.4), Motor vehicles (C.5), Petroleum and oil products (C.6), Health industry (C.7).

Table 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 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 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 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 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 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

D Description of European factor-saving technical change

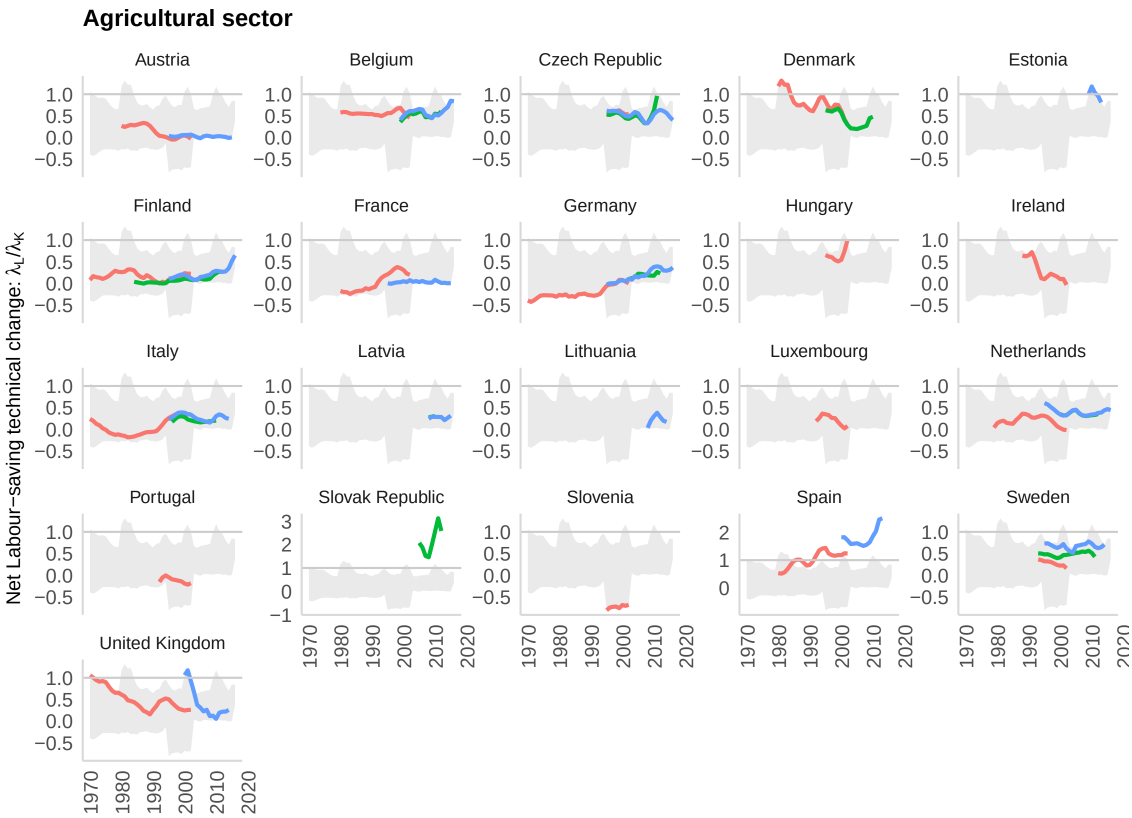
D.A Agricultural and Financial sectors in Europe — net labour-saving trends

We take the example of the agricultural and financial sectors in European countries[38] 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 9 in section 5.2).

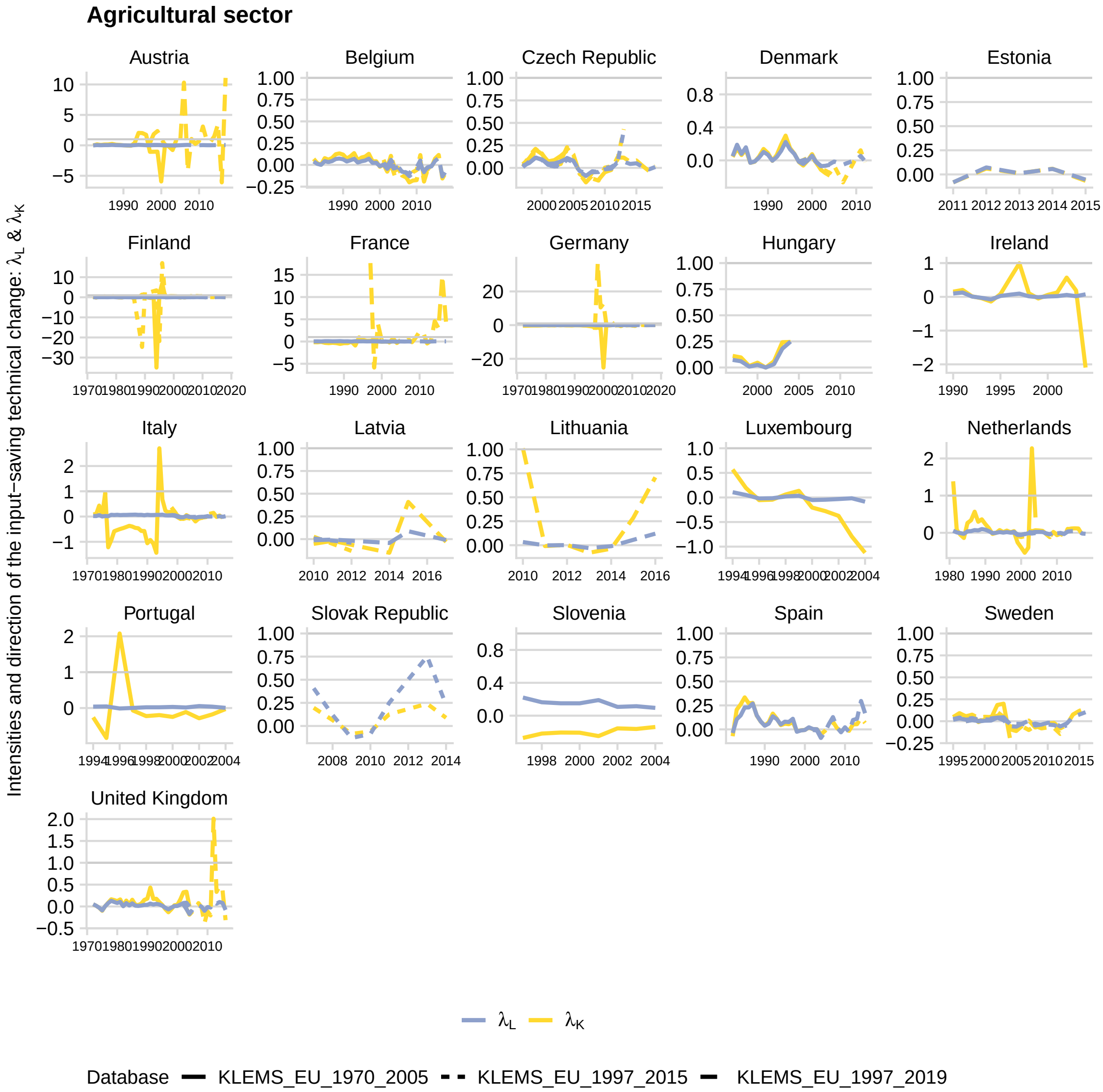
[38] SIC: "J-FINANCIAL INTERMEDIATION" and NACE: "K-Financial and insurance activities".

Figure D.10: Net Labour-saving technical change (λ_L/λ_K) in the Agricultural sector for 21 European countries



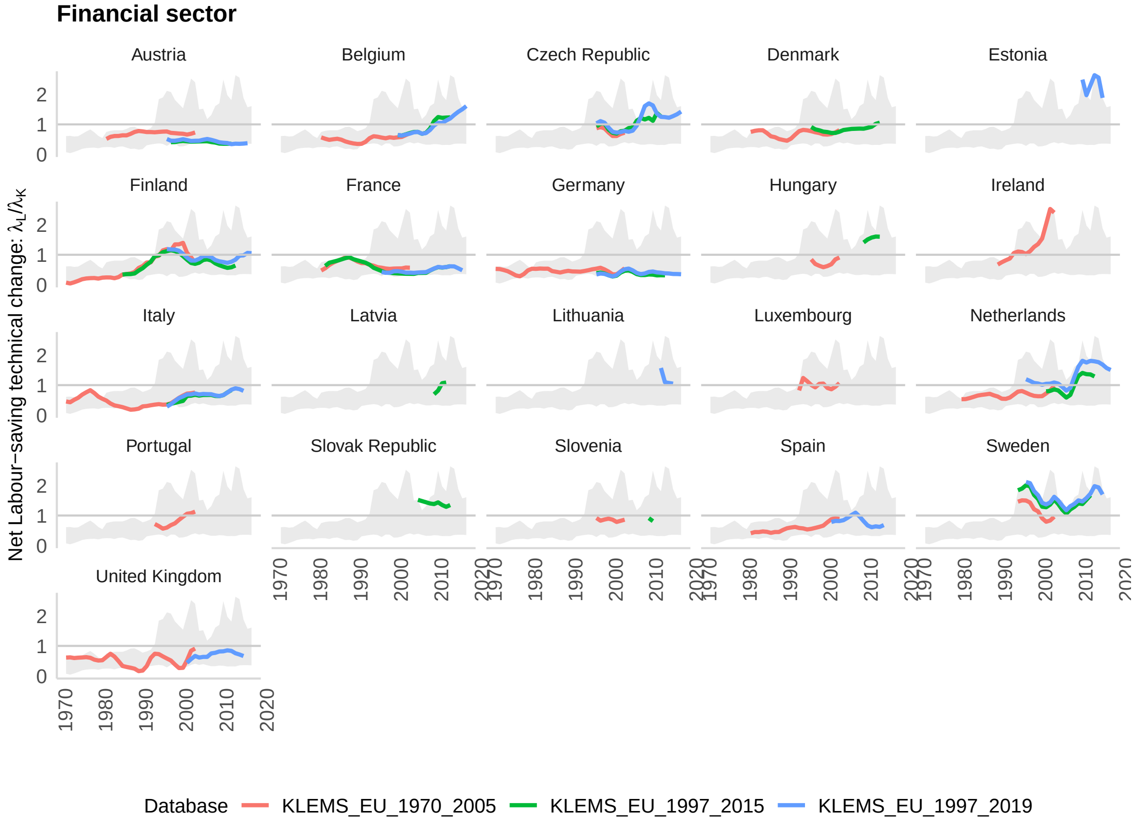
Databases: KLEMS v2008 (1970-2005), EU+ KLEMS v2017 (1997-2015) and v2021 (1997-2019)

Figure D.11: 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 D.12: Net Labour-saving technical change (λ_L/λ_K) in the Financial sector for 21 European countries

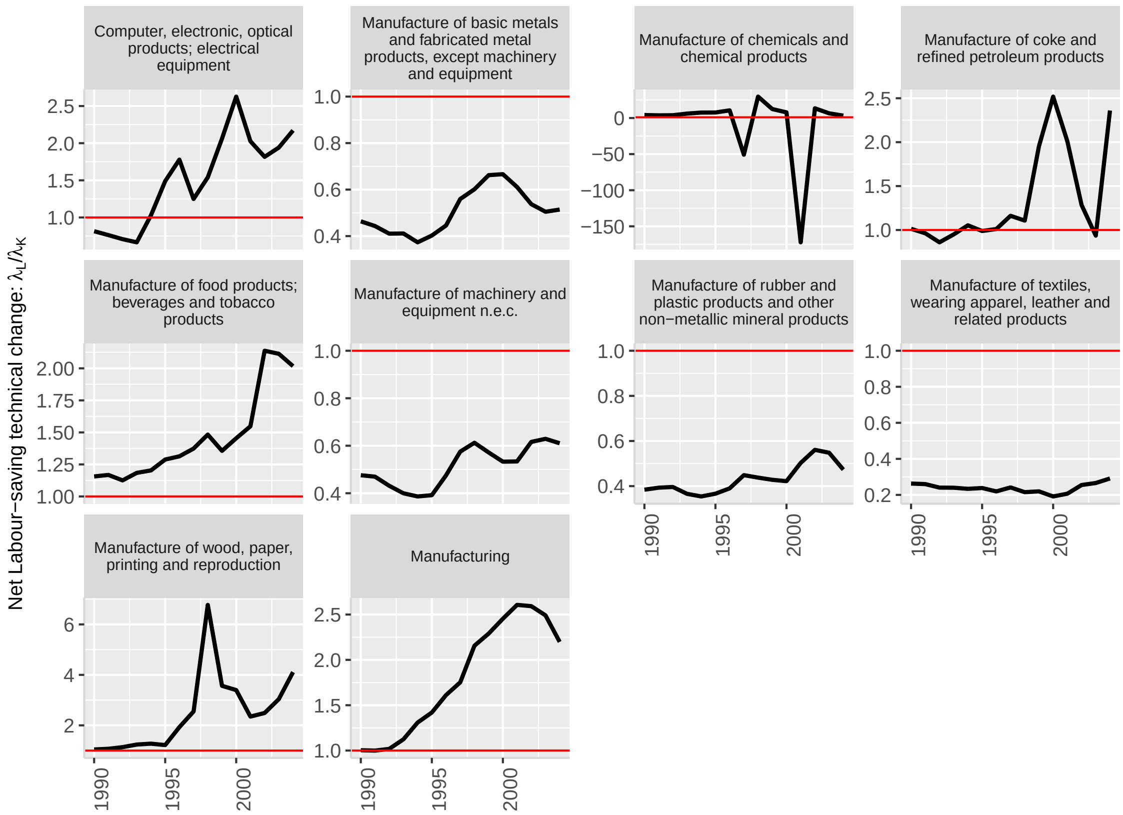


Databases: KLEMS v2008 (1970-2005), EU+ KLEMS v2017 (1997-2015) and v2021 (1997-2019)

D.B 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 D.13: Net Labour-saving technical change (λ_L/λ_K) in Ireland



Database: EU+ KLEMS v2017 (1997-2015)

D.C 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 D.14): 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 D.14: Aggregate direction of the technical change of the U.S. economy

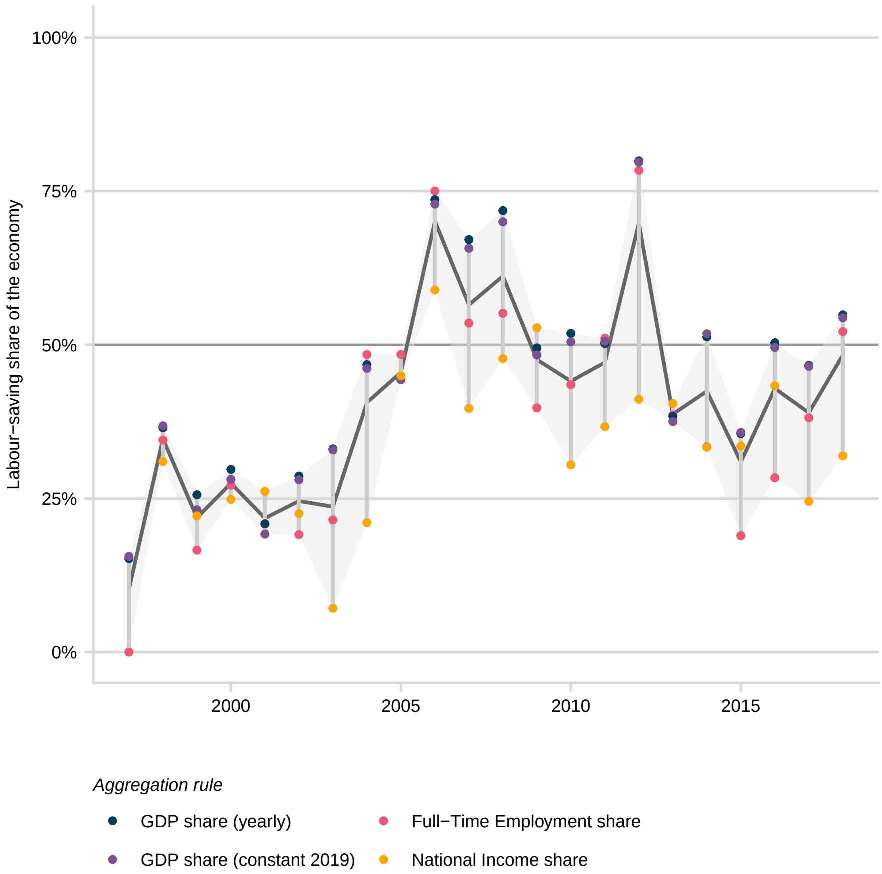
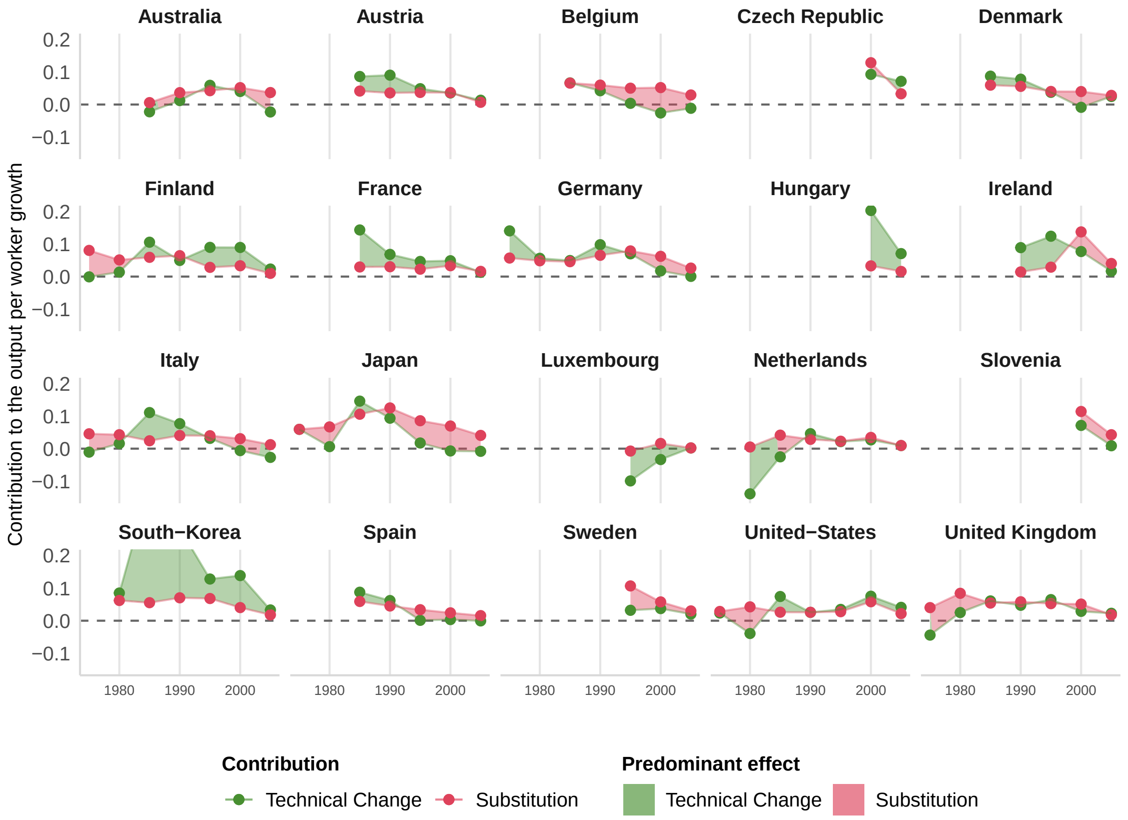


Figure D.15 shows the decomposition of growth in national value-added per worker into technical change and substitution of capital for labour, over 1970-2005 for 20 economies. In the United States and the United Kingdom, the technical change and substitution components were very close to each other in the 1980s and 1990s. In 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.[39] 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).

[39] 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 D.15: Substitution *vs* technical change component of output per worker growth at the national level 1970-2005

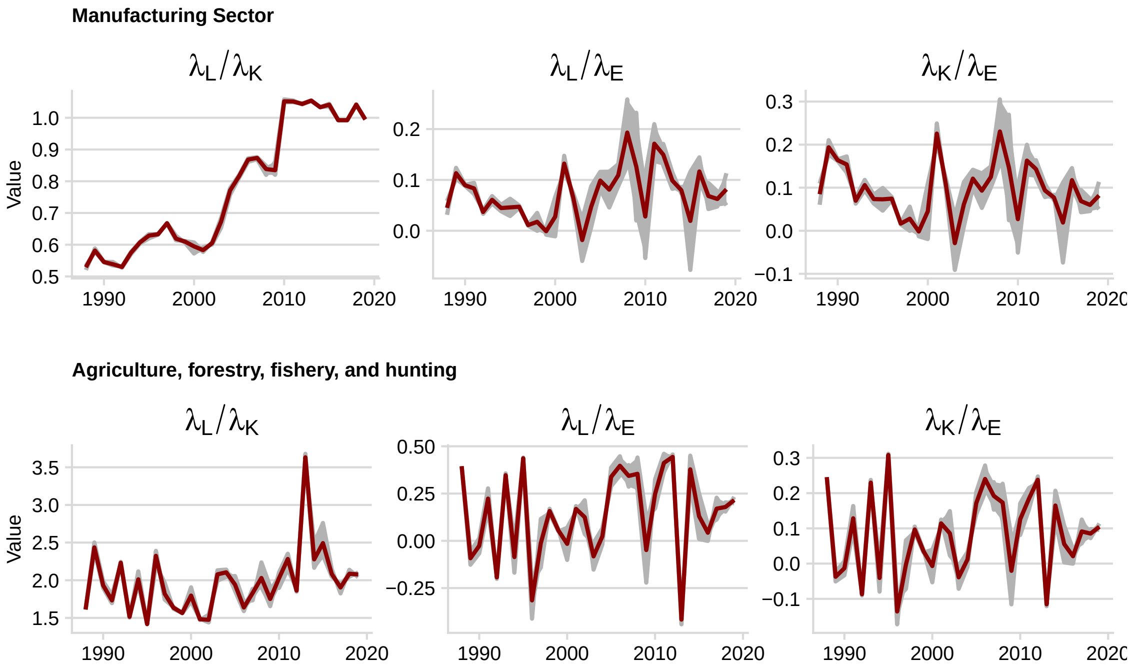


Note: The growth of output per worker is the sum of these two components. The predominant effect on the output per worker growth is considered to be the largest in absolute value. For clarity, data are aggregated at the 5Y timespan.

E Robustness to adding more inputs

In E.16, we show that the bias of technical change is robust to adding more inputs in the US KLEMS database. This result holds as well when computing the bias of technical change in the frameworks with i) capital, labour, electricity and fossil fuel, and ii) capital, low skills labour, medium skills, high skills labour, electricity and fossil fuel. The value and fluctuations of technical change intensities are similar in the two frameworks.

Figure E.16: Technical change bias is similar between framework when adding inputs

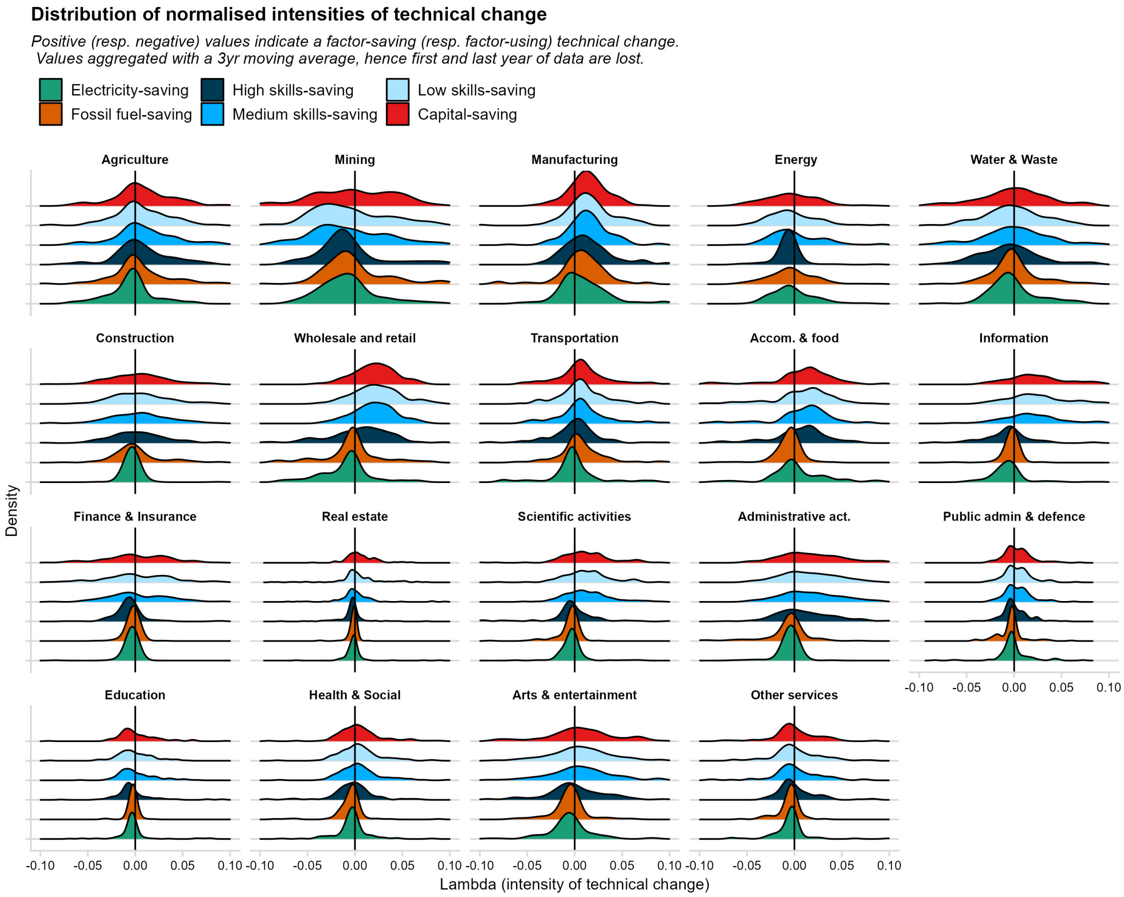


Database: US KLEMS (1990-2019). We compare three framework with more or less inputs: i) capital and labour (KL), ii) capital, labour and energy, iii) capital, labour, energy, material and services. Agriculture and Manufacturing are plotted, but this results is robust in other sectors as well.

F Skills and labour bias of green technical change

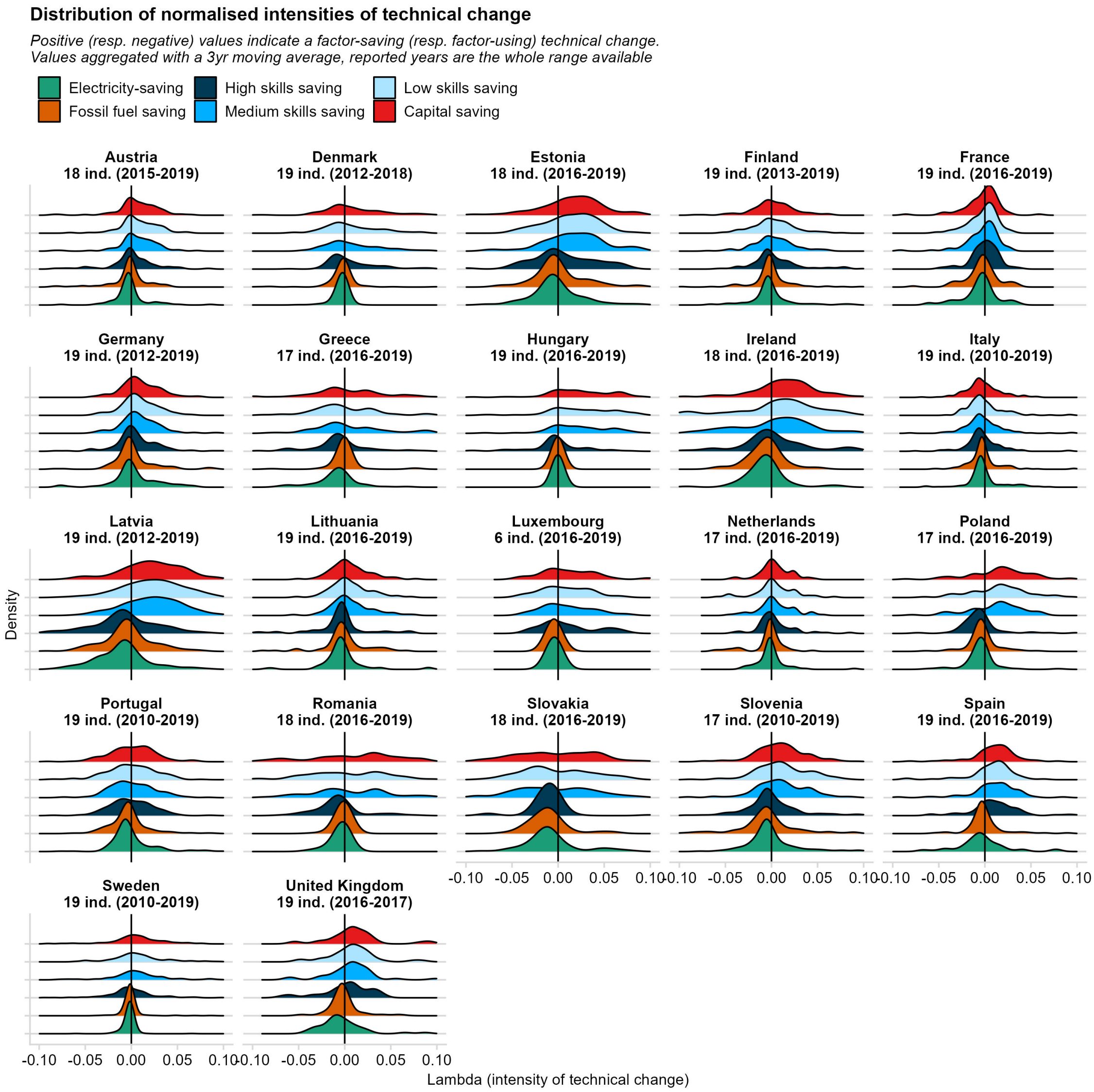
F.A Cross-country and cross-industry distribution of λs

Figure F.17: Distribution of λs, factor-saving intensities of technical change per factor and industry



Database: US KLEMS (1990-2019).

Figure F.18: Distribution of λs, factor-saving intensities of technical change per factor and country



Database: US KLEMS (1990-2019).

F.B Correlation between λs fluctuations

Figure F.19: Regression of $\Delta\lambda_{\text{fossil}} \sim \Delta\lambda_{\text{L}} + \Delta\lambda_{\text{K}} + \Delta\lambda_{\text{elec}} + I_{\text{country}} + I_{\text{sector}}$. 1Y data. Long series only (n>=8), Lambdas normalised by their alpha. First interval is 95%, second is 99%. Trim valued (within [-1,1]).

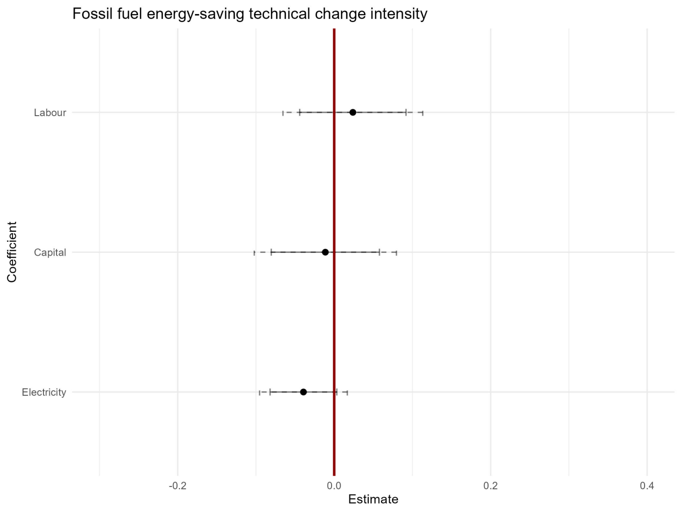


Figure F.20: Regression of $\Delta\lambda_K \sim \Delta\lambda_{\text{L}} + \Delta\lambda_{\text{fossil}} + \Delta\lambda_{\text{elec}} + I_{\text{country}} + I_{\text{sector}}$. 1Y data. Long series only (n>=8), Lambdas normalised by their alpha. First interval is 95%, second is 99%. Trim valued (within [-1,1]).

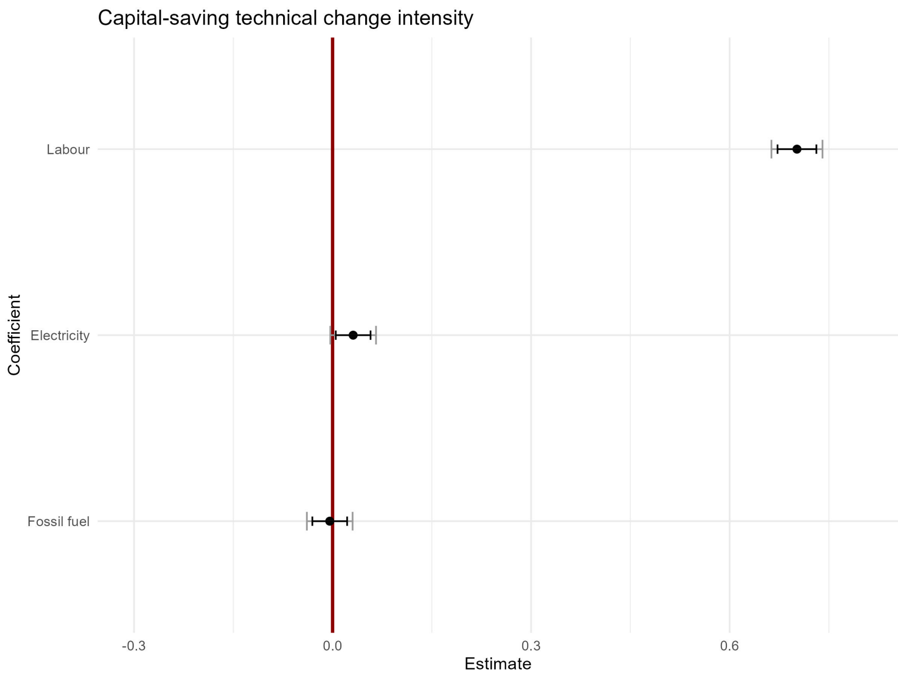


Figure F.21: Regression of $\Delta\lambda_K \sim \Delta\lambda_{\text{LS}} + \Delta\lambda_{\text{MS}} + \Delta\lambda_{\text{HS}} + \Delta\lambda_{\text{fossil}} + \Delta\lambda_{\text{elec}} + I_{\text{country}} + I_{\text{sector}}$. 1Y data. Long series only (n>=8), Lambdas normalised by their alpha. First interval is 95%, second is 99%. Trim valued (within [-1,1]).

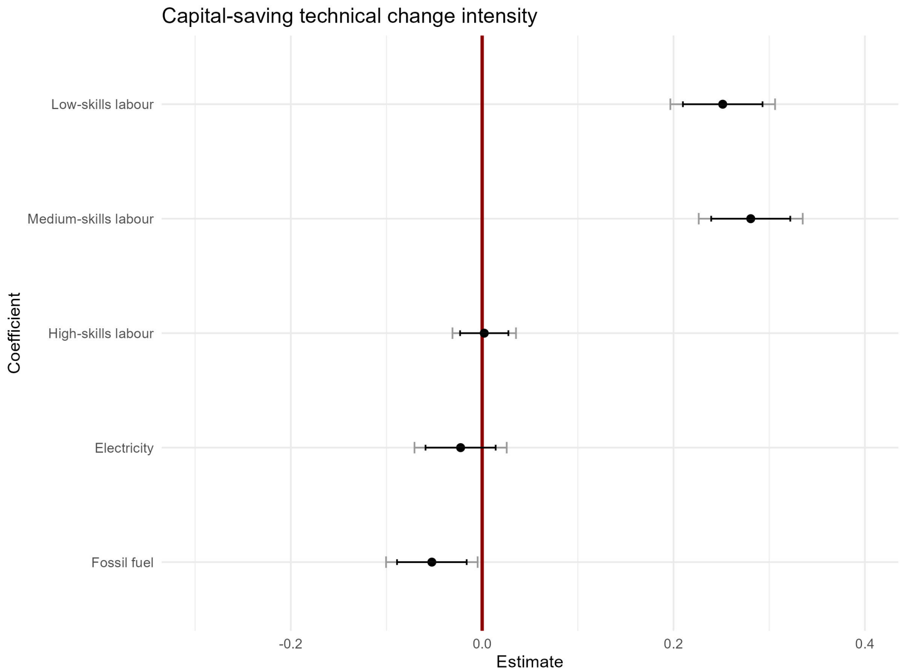


Figure F.22: Regression of $\Delta\lambda_{\text{elec}} \sim \Delta\lambda_{\text{L}} + \Delta\lambda_{\text{K}} + \Delta\lambda_{\text{fossil}} + I_{\text{country}} + I_{\text{sector}}$. 1Y data. Long series only (n>=8), Lambdas normalised by their alpha. First interval is 95%, second is 99%. Trim valued (within [-1,1]).

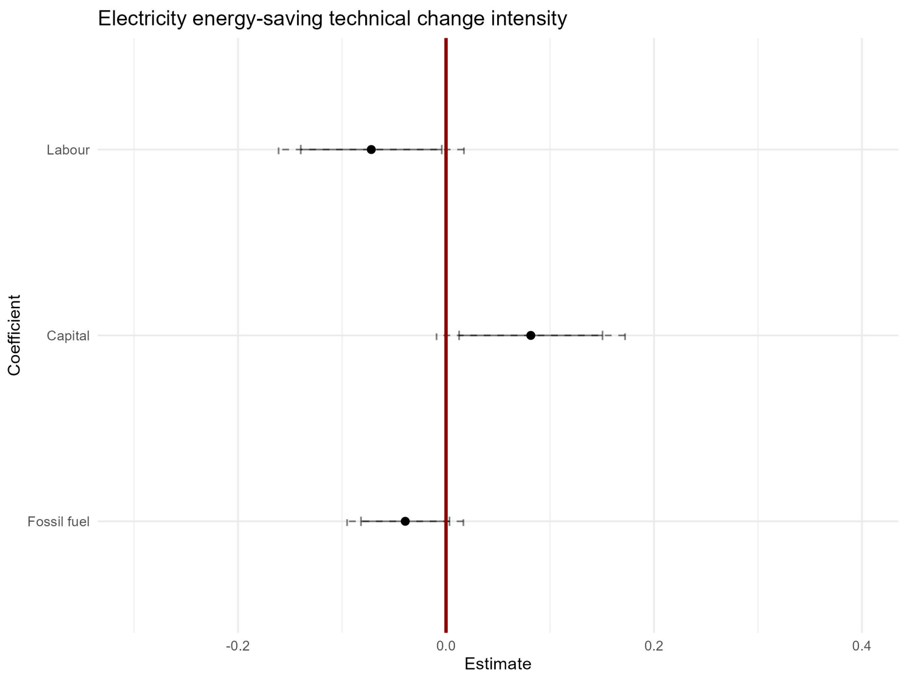


Figure F.23: Regression of $\Delta\lambda_{\text{elec}} \sim \Delta\lambda_{\text{LS}} + \Delta\lambda_{\text{MS}} + \Delta\lambda_{\text{HS}} + \Delta\lambda_{\text{K}} + \Delta\lambda_{\text{fossil}} + I_{\text{country}} + I_{\text{sector}}$. 1Y data. Long series only (n>=8), Lambdas normalised by their alpha. First interval is 95%, second is 99%. Trim valued (within [-1,1]).

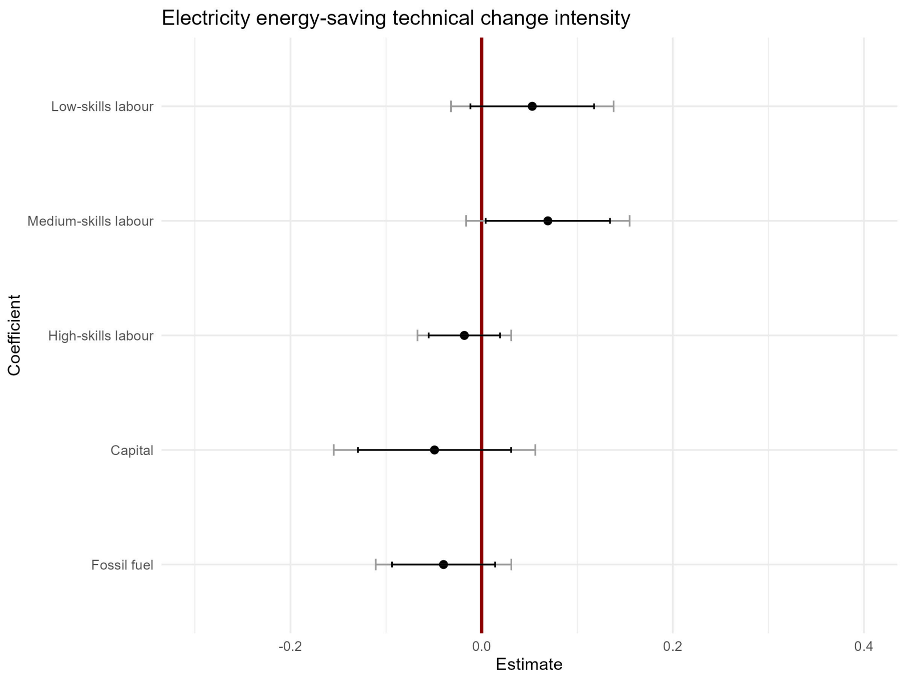


Table F.8: Correlation between the fluctuations in technical change intensity

	Dependent Variable: $\Delta\lambda_{\text{fossil}}$									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\Delta\lambda_{\text{LS}}$	-0.023					-0.045			0.059	0.033
	(0.042)					(0.043)			(0.057)	(0.039)
$\Delta\lambda_{\text{MS}}$		0.156^{*}					0.095		0.097	0.035
		(0.092)					(0.102)		(0.102)	(0.053)
$\Delta\lambda_{\text{HS}}$			0.053					0.047	0.086^{**}	0.138^{***}
			(0.043)					(0.043)	(0.044)	(0.020)
$\Delta\lambda_{\text{elec}}$				-0.035		-0.034	-0.033	-0.013	-0.013	-0.032
				(0.040)		(0.040)	(0.039)	(0.041)	(0.040)	(0.026)
$\Delta\lambda_{\text{K}}$					0.306^{***}	0.312^{***}	0.164	0.328^***	0.157	0.016
					(0.111)	(0.115)	(0.122)	(0.110)	(0.120)	(0.069)
Fixed effects Country	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	865	861	849	852	863	850	846	836	832	1,690
R^2	0.004	0.007	0.008	0.004	0.012	0.013	0.009	0.019	0.021	0.039

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

The first 9 columns include more or less variables, and are restricted to Country × Industry with more than 9 years of data. The 10th columns is only restricted to times series longer than 3 years.

G Testing for Hicks's hypothesis

In this section, we propose and estimate alternative specifications of Hicks' hypothesis.

G..1 Specifications

In this section, we propose 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:
$$\frac{\lambda_L}{\lambda_K} \sim \Delta\frac{w}{r} \iff \frac{\lambda_L}{\lambda_K} = a_{w/r}^{L/K}\Delta\left(\frac{w}{r}\right) + \varepsilon, \tag{26}$$
with $a_{w/r}^{L/K}$ the estimated coefficient;
- or the relationship between the relative direction of technical change and the evolution of prices
$$\frac{\lambda_L}{\lambda_K} \sim \Delta w + \Delta r \iff \frac{\lambda_L}{\lambda_K} = a_w^{L/K}\Delta w + a_r^{L/K}\Delta r + \varepsilon, \tag{27}$$
with $a_r^{L/K}$ and $a_w^{L/K}$ the estimated coefficients;
- or, the relationship between each direction of technical change and the evolution of relative prices
$$\begin{aligned} \lambda_L \sim \Delta\frac{w}{r} \iff &\quad \lambda_L = a_{w/r}^L\Delta\frac{w}{r} + \varepsilon \\ \lambda_K \sim \Delta\frac{w}{r} \iff &\quad \lambda_K = a_{w/r}^K\Delta\frac{w}{r} + \varepsilon, \end{aligned} \tag{28}$$
with $a_{w/r}^L$ and $a_{w/r}^K$ the estimated coefficients;
- or finally, the intensity of technical change separately:
$$\begin{aligned} \lambda_L \sim \Delta w + \Delta r \iff &\quad \lambda_L = a_w^L\Delta w + a_r^L\Delta r + \varepsilon \\ \lambda_K \sim \Delta w + \Delta r \iff &\quad \lambda_K = a_w^K\Delta w + a_r^K\Delta r + \varepsilon, \end{aligned} \tag{29}$$
with a_w^L, a_r^L, a_w^K and a_r^K the estimated coefficients.

G..2 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**: $a_w^{L/K} > 0$ (eq. 27), **Results**: section 7.3
Equation: $a_w^L > a_w^K$ (eq. 29), **Results**: section G.E
2. A relative increase in the cost of labour leads to relatively labour-saving technical change:
Equation: $a_{w/r}^{L/K} > 0$ (eq. 26), **Results**: section G.C
Equation: $(a_w^L - a_w^K)/(a_r^L - a_r^K) > 1$ (eq. 29), **Results**: section G.E
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: $a_w^L > 0$ or $a_w^K < 0$ (eq. 29), **Results**: section G.D

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. 29), **Results**: section G.E
   Equation: $a^L_{w/r} > 0$ (eq. 28), **Results**: appendix G.H.[40]

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: whether an increase in wages triggers more labour-saving than capital-saving technical change.

The results are summarised in section 7.4 to provide an overview on Hicks's hypothesis.

G.A Intrinsic bias of 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:

$$\frac{\partial \lambda_L}{\partial w_1} = \frac{L_0}{Y_0 - r_1 K_0} \tag{30}$$

$$\frac{\partial \lambda_K}{\partial w_1} = \frac{r_1 L_0 K_0}{(Y_0 - w_1 L_0)^2}. \tag{31}$$

The following equation

$$\frac{\partial \lambda_L}{\partial w_1} - \frac{\partial \lambda_K}{\partial w_1} = \frac{L_0}{Y_0 - r_1 K_0} - \frac{r_1 L_0 K_0}{(Y_0 - w_1 L_0)^2} = 0 \tag{32}$$

has two roots:

$$w_m = \frac{Y_0}{L_0} - \sqrt{\frac{K_0 r_1 Y_0 - K_0^2 r_1^2}{L_0^2}} \tag{33}$$

$$w_M = \frac{Y_0}{L_0} + \sqrt{\frac{K_0 r_1 Y_0 - K_0^2 r_1^2}{L_0^2}}. \tag{34}$$

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).*

[40]We present the estimation of (28) in the appendices and only discuss it briefly in the main text.

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 $\alpha_L = \dfrac{w_0 L_0}{Y_0} = \dfrac{1}{x}$ with $x >= 1$. Thus, we can write: $Y_0 = x w_0 L_0$ and $r_0 K_0 = Y_0 \dfrac{x-1}{x}$.

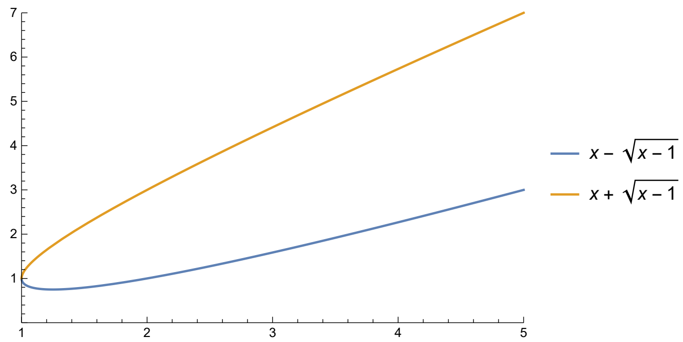
We can rewrite w_m and w_M, the roots of the equation (32) (Lemma 3), as functions of x:

$$w_m = w_0 \left(x - \sqrt{x-1}\right) \tag{35}$$
$$w_W = w_0 \left(x + \sqrt{x-1}\right) \tag{36}$$

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.G.24) 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 $\frac{\partial \lambda_L}{\partial w_1} < \frac{\partial \lambda_K}{\partial w_1}$.

Figure G.24: Roots of equation (32) against the inverse of the labour-share



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. $\square$

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 my reference hypothesis for this section, is that a very labour-intensive sector will tend to save on labour if the price of labour rises.

G.B Price variations on relative technical change

This section complements the section 7.3 and present the data in table G.9 and the salient industries in table G.10.

Table G.9: 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

Table G.10: 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

G.C Relative price variations effect on relative technical change

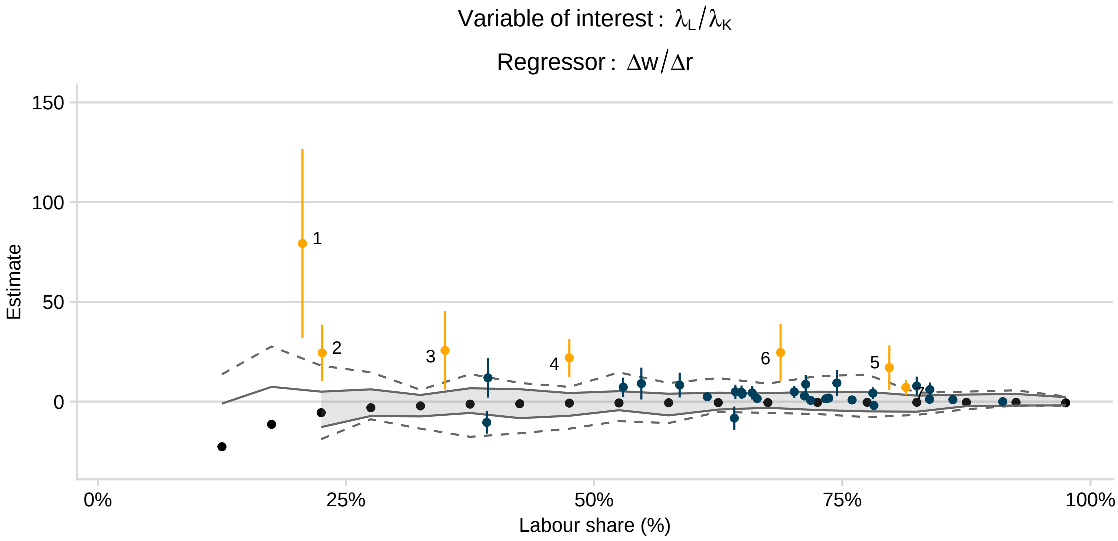
Estimated equation We estimate the coefficient $a_{w/r}^{L/K}$ of equation (26), that we rewrite below:

$$\frac{\lambda_L}{\lambda_K} \sim \Delta \frac{w}{r} \iff \frac{\lambda_L}{\lambda_K} = a_{w/r}^{L/K} \Delta \left(\frac{w}{r} \right) + \varepsilon.$$

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.

Figure G.25: 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 14. The numbered legends identifying the sectors highlighted in yellow correspond to the legends in Table G.11.

Salient industries Seven industries show estimates significantly more positive than randomly generated data (Figure G.25). They represent 19.4% of all significant estimates. These industries are detailed in table G.11. 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.

Table G.11: 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

G.D Price variations effect on technical change

Estimated equation We estimate the coefficient a^L_w, a^L_r, a^K_w and a^K_r of equation 29, that we rewrite below:

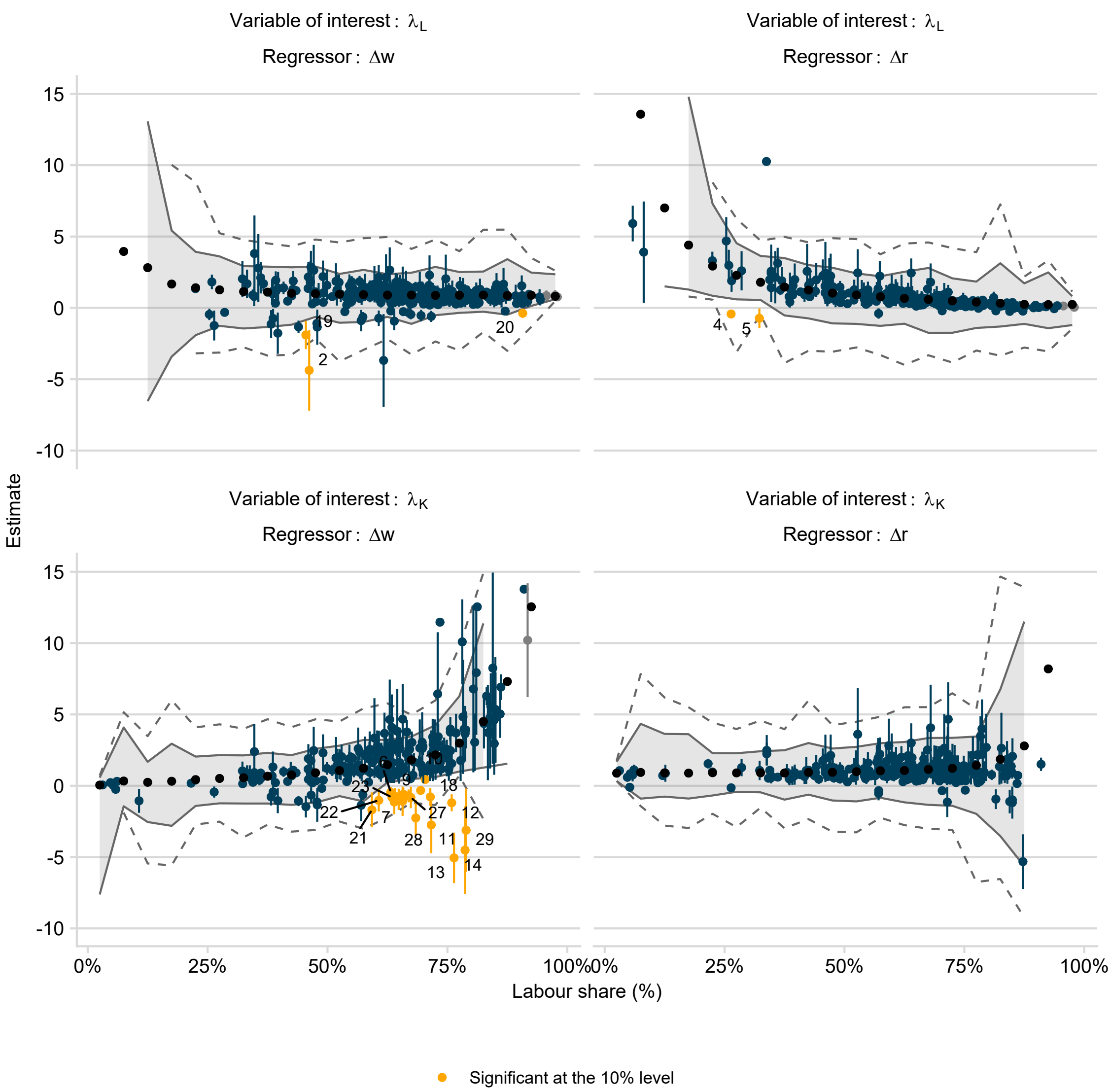
$$\lambda_L \sim \Delta w + \Delta r \iff \quad \lambda_L = a^L_w \Delta w + a^L_r \Delta r + \varepsilon$$
$$\lambda_K \sim \Delta w + \Delta r \iff \quad \lambda_K = a^K_w \Delta w + a^K_r \Delta r + \varepsilon,$$

Significance of the results The instrumentation and estimation results for equation are described in Table G.12. 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 G.I.

Table G.12: 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

Figure G.26: 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 (29) 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 G.13.
Data: KLEMS US (1986-2019), KLEMS EU+ v2021 (1997-2019), KLEMS EU+ v2017 (1997-2015), KLEMS EU+ v2008 (1970-2005)

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 G.13) 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.[41] The industries and countries represented are sufficiently varied to ensure that my results are not due to a single systematic bias.

Table G.13: 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 G.26. Including them would make the graph difficult to read. For an analysis of these points see the appendix G.32 and figure G.32.

G.E Alternative estimate of the (relative) price variations effect on (relative) technical change

We can use the coefficients of the equation (29) to estimate the effects of a relative increase in price on technical change intensities (as in eq. (28), appendix G.H) or the effect of an increase in price on the relative technical change (as in eq. (27), section 7.3).

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 G.27 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

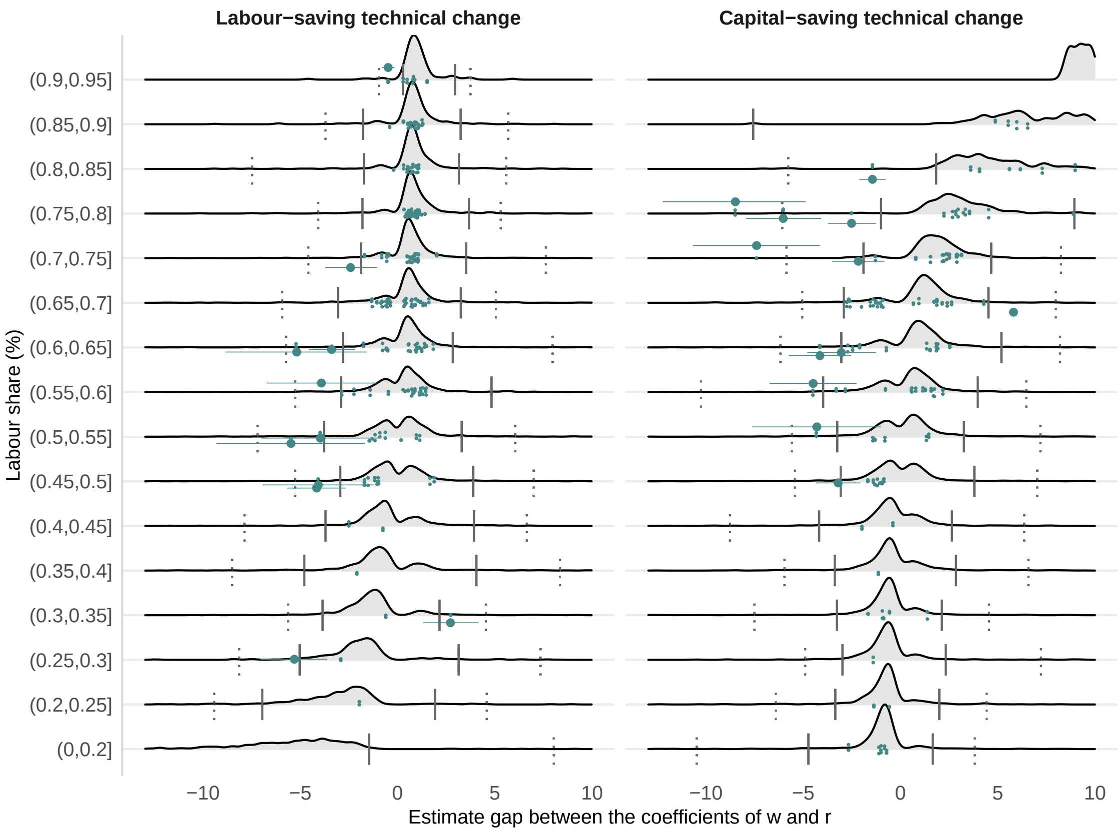
[41] Note that the manufacturing sectors are less sensitive to errors in the measurement of labour and capital flows than the services for example. It does add to the level of confidence to be given to these results.

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.[42]

For a number of real industries, the difference between the coefficients is significantly different from the one predicted by the randomly generated data (Figure G.27).[43] 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.[44] This effect is in line with Hick's hypothesis.

Figure G.27: 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 (28). 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)

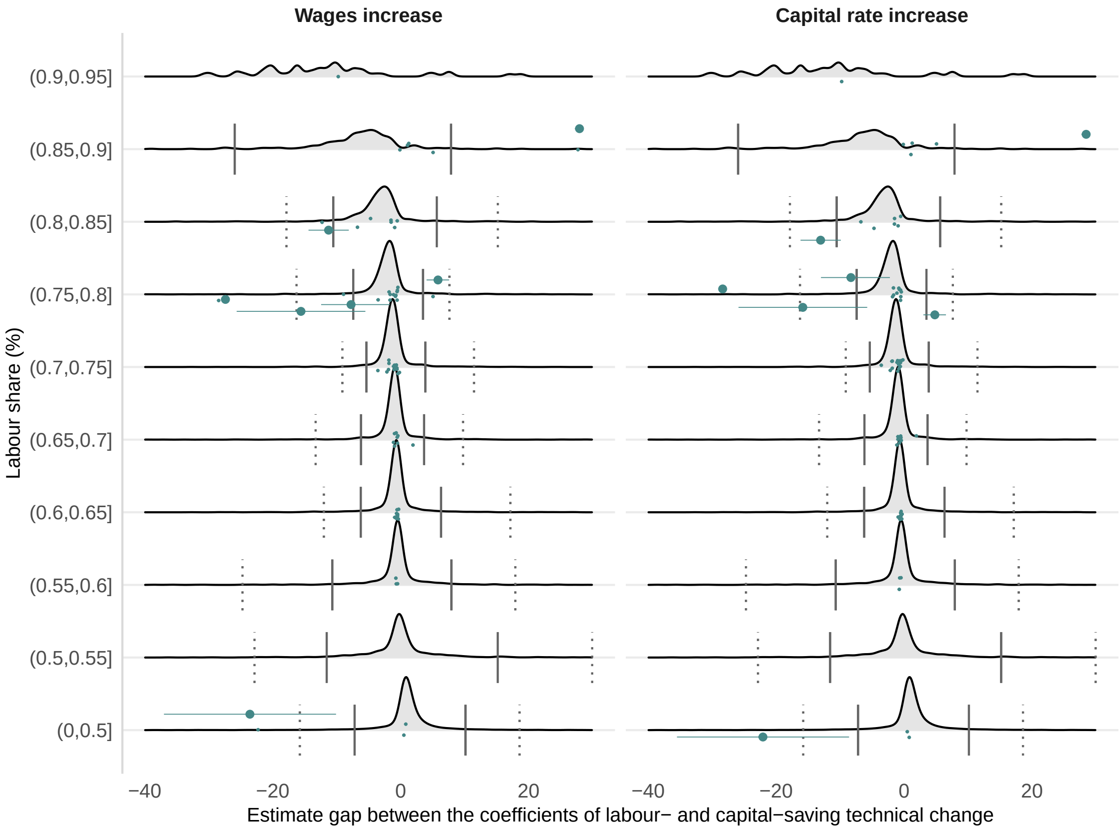
[42]Hence the two-peak shape around 0, since a gap of 0 is qualified by two coefficients not statistically different from each other.

[43]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.

[44]$\lambda_K \sim (\Delta w - \Delta r)$ shows a negative correlation. Thus the reaction in r is greater than that in w.

Secondly, we study the difference between the coefficients $a^L_w - a^K_w$ (resp. $a^L_r - a^K_r$). 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 G.28) for both $a^L_w - a^K_w$ (left panel) and $a^L_r - a^K_r$ (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.

Figure G.28: 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 (28). Respectively the quantities plotted are $a^L_w - a^K_w$ (left) and $a^L_r - a^K_r$ (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)

G.F Prices variations on the bias of technical change (difference of lambdas

Selection of the difference of lambdas and not the ratio One advantage: we can consider the difference of lambdas like the bias of technical change no matter the sign of the lambdas. One main problem is that the difference reflects poorly the relative variation in the intensities of technical change.

Specification Nevertheless, we can use the same instruments for the sectoral prices and the same specification for the difference in lambdas than for their ratio.

We add a couple specification without outliers, and it works better. We also try using the price of the total economy when available in KLEMS (all but the US KLEMS 1986-2019) to complement the weighted average of prices. It works no better.

Estimated equation We estimate the coefficients a_r^{L-K} and a_w^{L-K} in the following equation

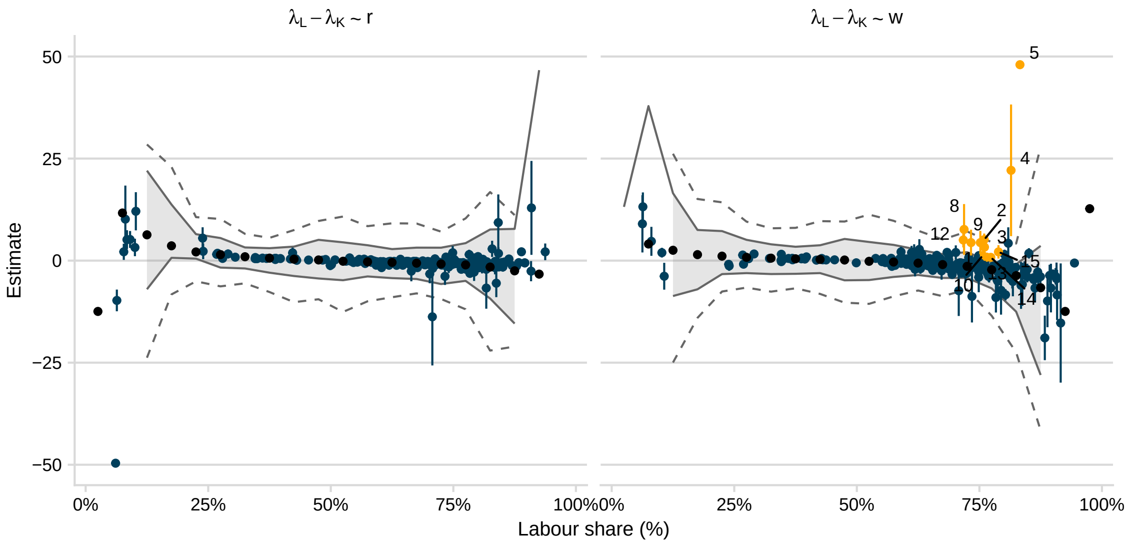
$$\lambda_L - \lambda_K \sim \Delta w + \Delta r \Longleftrightarrow \lambda_L - \lambda_K = a_w^{L-K}\Delta w + a_r^{L-K}\Delta r + \varepsilon. \tag{37}$$

NB: we also estimate the equation (37) with only one price at a time

$$\begin{cases} \lambda_L - \lambda_K & \sim \Delta w \\ \lambda_L - \lambda_K & \sim \Delta r \end{cases}$$

Significance of the results The number of industries series with significant results for all these test is summarised in Table G.9. Only 3% of all the time series available have strong instrumentation, of which 50% yield significant relationship between the difference in lambdas and the prices.

Figure G.29: Estimation of the relationship between the bias of technical change($\lambda_L - \lambda_K$) 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 (37) over 40,000 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 G.14.
Data: KLEMS US (1986-2019), KLEMS EU+ v2021 (1997-2019), KLEMS EU+ v2017 (1997-2015), KLEMS EU+ v2008 (1970-2005)

Results

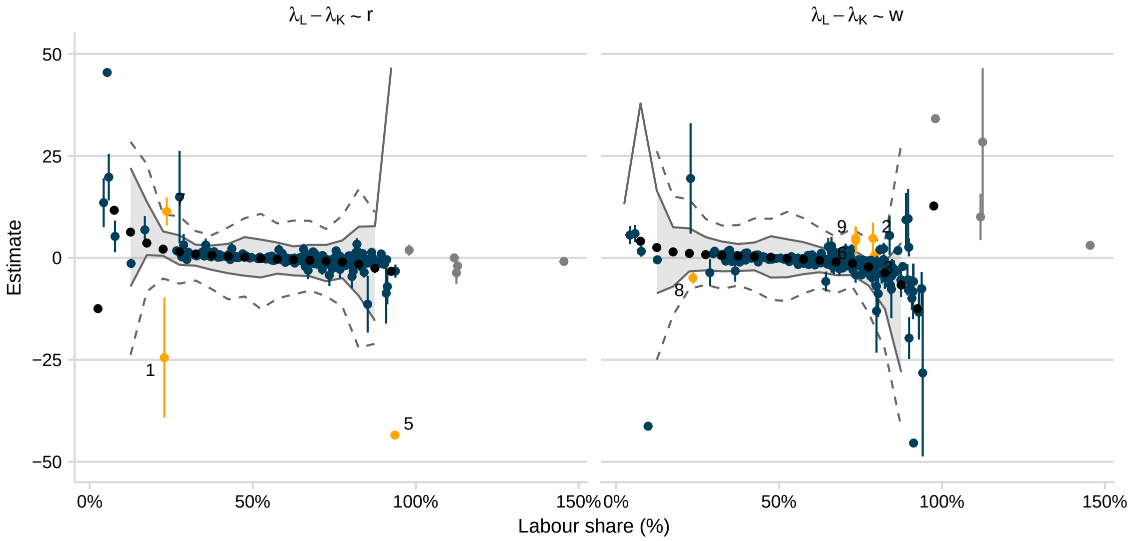
Salient industries 15 industries (Table G.14) have estimates of a_w^{L-K} significantly different than the estimates on randomly generated data. Except for one point (7), all the significant points are between the bias of technical change and the variations of labour prices. Except for one (6), these relationship are positive.[45]. These points represent varied industries: manufacturing, retail, health, IT and agriculture, mostly in more recent years and European Western countries.

Table G.14: Industries for which the bias of technical change ($\lambda_L - \lambda_K$ 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	Austria	25	Rubber and plastics
2	KLEMS EU+ v2008	United Kingdom	26	Other non-metallic mineral
3	KLEMS EU+ v2008	Austria	17t19	Textiles, textile , leather and footwear
4	KLEMS EU+ v2008	France	N	Health and social work
5	KLEMS EU+ v2008	Finland	AtB	Agriculture, hunting, forestry and fishing
6	KLEMS EU+ v2008	Germany	52	Retail trade, except of motor vehicles and motorcycles; repair of household goods
7	KLEMS EU+ v2017	France	31-33	Other manufacturing; repair and installation of machinery and equipment
8	KLEMS EU+ v2017	Austria	31-33	Other manufacturing; repair and installation of machinery and equipment
9	KLEMS EU+ v2017	France	62-63	IT and other information services
10	KLEMS EU+ v2017	Sweden	47	Retail trade, except of motor vehicles and motorcycles
11	KLEMS EU+ v2017	France	31-33	Other manufacturing; repair and installation of machinery and equipment
12	KLEMS EU+ v2021	Austria	C31-C33	Manufacture of furniture; jewellery, musical instruments, toys; repair and installation of machinery and equipment
13	KLEMS EU+ v2021	Belgium	R-S	Arts, entertainment, recreation; other services and service activities, etc.
14	KLEMS EU+ v2021	EU12 without UK	G	Wholesale and retail trade; repair of motor vehicles and motorcycles
15	KLEMS EU+ v2021	Germany	C24-C25	Manufacture of basic metals and fabricated metal products, except machinery and equipment

Note: See the associated figure G.29. 3 points (6,7,11) are not present on the graph because they are too big values, (about -200 for points 6 and 7, respectively on Δw and Δr, and about 200 for point 11 on Δw. The point 7 is the only significant one on Δr.

Figure G.30: Estimation of the relationship between the bias of technical change($\lambda_L - \lambda_K$) and price variation ($\Delta w, \Delta r$) with data aggregated on a 5 year rolling mean



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 (27) 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 G.10.
Data: KLEMS US (1986-2019), KLEMS EU+ v2021 (1997-2019), KLEMS EU+ v2017 (1997-2015), KLEMS EU+ v2008 (1970-2005)

[45] Points 6 and 7 are French other manufacturing.

Table G.15: Industries for which the bias of technical change ($\lambda_L - \lambda_K$ and price variations ($\Delta w, \Delta r$) is significantly different from the relationship estimated on randomly generated series - aggregated time series within a 5Y rolling windows

Legend	Scope	Country	Industry code	Industry
1	KLEMS EU+ v2008	Spain	23	Coke, refined petroleum and nuclear fuel
2	KLEMS EU+ v2008	Spain	H	Hotels and restaurants
3	KLEMS EU+ v2008	Denmark	27t28	Basic metals and fabricated metal
4	KLEMS EU+ v2008	Spain	52	Retail trade, except of motor vehicles and motorcycles; repair of household goods
5	KLEMS EU+ v2017	Finland	I	Accommodation and food service activities
6	KLEMS EU+ v2017	Finland	45	Wholesale and retail trade and repair of motor vehicles and motorcycles
7	KLEMS EU+ v2021	Sweden	J61	Telecommunications
8	KLEMS EU+ v2021	Sweden	J61	Telecommunications
9	KLEMS EU+ v2021	Spain	C31-C33	Manufacture of furniture; jewellery, musical instruments, toys; repair and installation of machinery and equipment

Note: See the associated figure G.30.

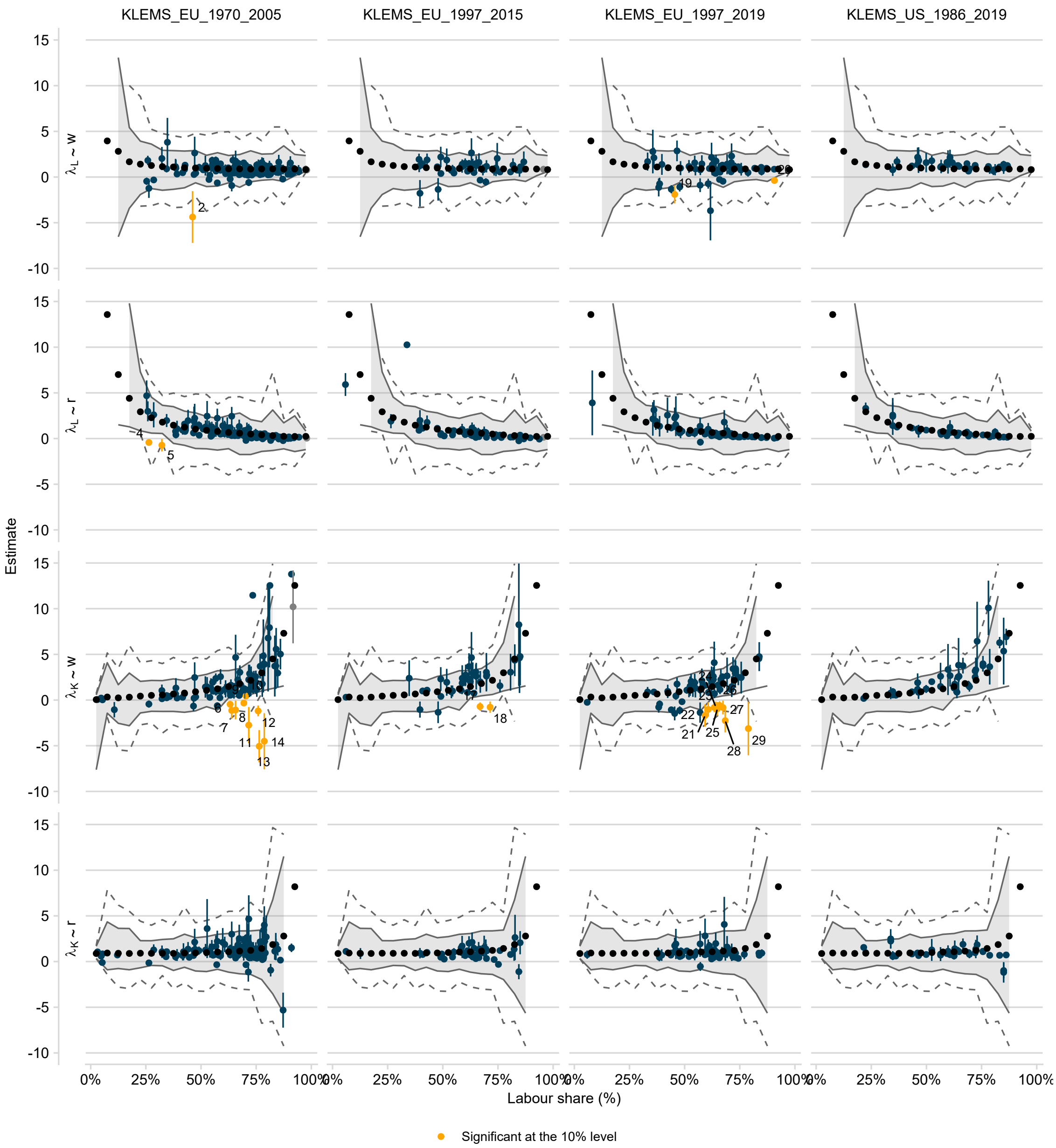
Using smoothed data with 5Y rolling mean

G.G $\lambda \sim \Delta r + \Delta w$ — Estimating the relationship between the intensity of technical change and prices

We refine the results discussed in section G.D.

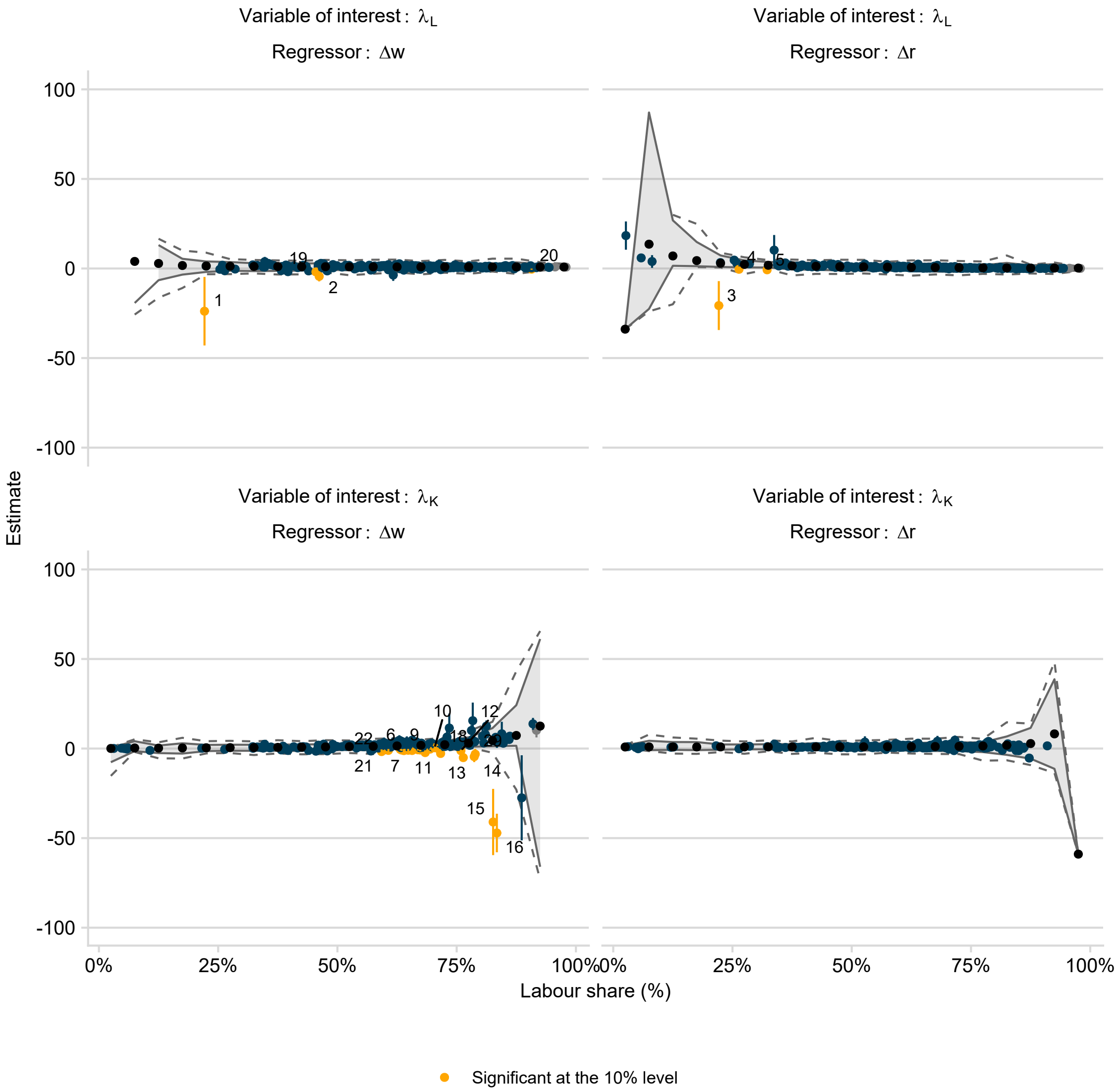
The results in Figure G.26 are broken down by database to show my results are not concentrated on one database. Note that we find no significant results for the U.S. in the KLEMS US NAICS (1986-2019) database .

Figure G.31: 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.



On the figure G.32 we see the 5 points constrained by the scale of the figure G.26. 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 G.32: 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.



G.H $\lambda \sim \Delta w/r$ — Estimating the relationship between the intensity of technical change and relative prices

Estimate of equation (28) $\lambda \sim \Delta \frac{w}{r}$ already discussed briefly in section G.C.

The estimation of λ on the variations of the relative prices of the inputs ($\Delta w/r$) from (28) gives very few significant results. Only two points differ from the estimations on randomly generated data (Table G.16). These two points show estimates of $a^K_{w/r}$ coefficients significantly negative (Figure G.33). 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.

Figure G.33: 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.

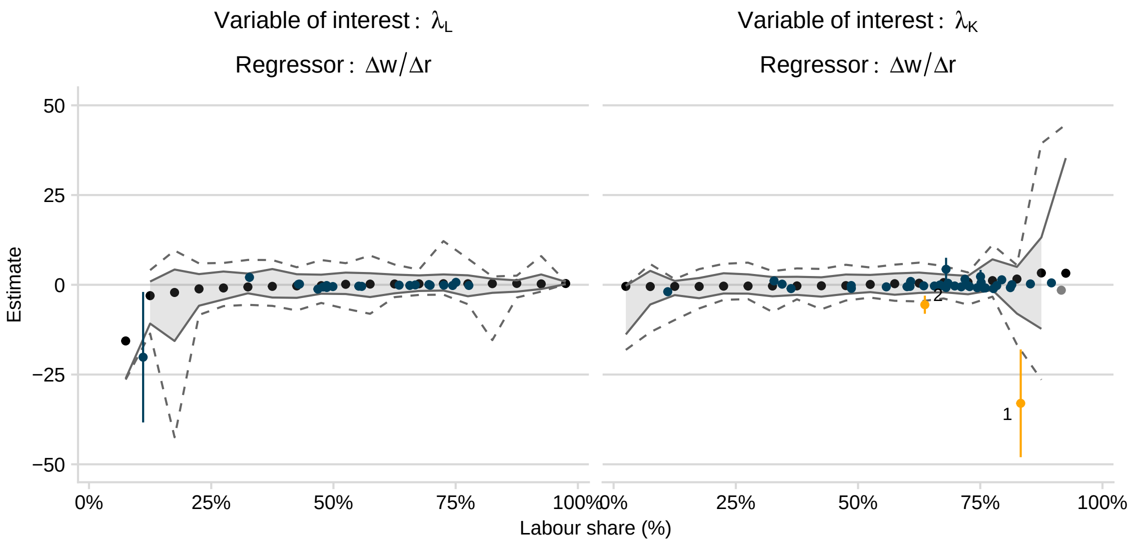


Table G.16: Industries for which the relationship between the intensity of technical change ($\lambda_{L,K}$) on relative price variations ($\Delta \frac{w}{r}$) is significantly different from the relationship estimated on randomly generated series

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

G.I Selected industries — Regressions tables

We include the regressions of the sectors we distinguish in Table G.13: equation 29. 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 G.17: 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	

Table G.18: 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 G.19: 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 G.20: 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 G.21: 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 G.22: 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 G.23: 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	

Table G.24: 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	

H Forecast labour share

H.A Basic principles

My framework, hereafter "Convex envelop 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.[46] 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.

H.B Training set — building the estimators

H.B.1 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;

$$\begin{aligned} \beta_L(t) &= \alpha_0 + \alpha_1 \beta_L(t-1) + \alpha_2 \beta_K(t-1) + \varepsilon \\ \beta_K(t) &= \alpha'_0 + \alpha'_1 \beta_L(t-1) + \alpha'_2 \beta_K(t-1) + \varepsilon \end{aligned} \tag{38}$$

- Or that the allocation depends only on the intensity and direction of technical change

$$\begin{aligned} \beta_L(t) &= \alpha_0 + \alpha_1 \lambda_L(t) + \alpha_2 \lambda_K(t) + \varepsilon \\ \beta_K(t) &= \alpha'_0 + \alpha_1 \lambda_L(t) + \alpha_2 \lambda_K(t) + \varepsilon \end{aligned} \tag{39}$$

- Or that the allocation depends both on past allocation and the intensity and direction of technical change

$$\begin{aligned} \beta_L(t) &= \alpha_0 + \alpha_1 \beta_L(t-1) + \alpha_2 \beta_K(t-1) + \alpha_3 \lambda_L(t) + \alpha_4 \lambda_K(t) + \varepsilon \\ \beta_K(t) &= \alpha'_0 + \alpha'_1 \beta_L(t-1) + \alpha'_2 \beta_K(t-1) + \alpha_3 \lambda_L(t) + \alpha_4 \lambda_K(t) + \varepsilon \end{aligned} \tag{40}$$

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 envelop" 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 (38), (39) or (40)
  $\beta_{K,L} = f(\lambda_K, \lambda_L, \beta_{K,L}(t-1))$
- **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:
  $Y_1 = r_1 K_1 + w_1 L_1$, $\alpha_L = f(K_1, L_1, Y_1, r_1, w_1)$.

[46] This assumption is relaxed in the course of the analysis.

Estimation of the drivers of βs We report the estimations of the βs prior to the forecast step for three sectors: Agriculture (table H.25), Manufacturing (table H.26), Paper products (table H.27) and Finance (table H.28).

Table H.25: 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 (39), (39), (40).

Table H.26: 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 (39), (39), (40).

Table H.27: 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 (39), (39), (40).

Table H.28: 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 (39), (39), (40).

H.B.2 CES

We calibrate the CES function for each industry, in the form of

$$F(K,L) = A\left(bK^{\frac{\sigma-1}{\sigma}} + (1-b)L^{\frac{\sigma-1}{\sigma}}\right)^{\dfrac{\sigma}{\sigma-1}}. \tag{41}$$

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
$$\ln\left(\left(\frac{w}{r}\right)_t\right) = \beta_0 + \beta_1 \ln\left(\left(\frac{K}{L}\right)_t\right) + \beta_2 \ln\left(\left(\frac{w}{r}\right)_{t-1}\right) + \varepsilon. \tag{42}$$

- If the first-difference series are stationery ($I(1)$), the short-term elasticity of substitution between capital and labour is β_1
$$\Delta\ln\left(\left(\frac{w}{r}\right)_t\right) = \beta_0 + \beta_1 \Delta\ln\left(\left(\frac{K}{L}\right)_t\right) + \varepsilon. \tag{43}$$

- 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

$$\Delta\ln\left(\left(\frac{w}{r}\right)_t\right) = \beta_0 + \beta_1 \Delta\ln\left(\left(\frac{K}{L}\right)_t\right) + \beta_2 \ln\left(\left(\frac{w}{r}\right)_{t-1}\right) + \beta_3 \ln\left(\left(\frac{K}{L}\right)_{t-1}\right) + \varepsilon. \tag{44}$$

We follow Klump and de La Grandville (2000) to calibrate the distribution parameter, building on Rutherford (1995) normalisation:

$$b = \pi_0 \left(\frac{Y_0}{K_0}\right)^{\rho} A^{\rho} \tag{45}$$

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 $\pi_0 = r_0K_0/Y_0$, 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).

My sigma estimates are reported in the appendix H, Figure H.34. My estimates are low, but plausible when compared to estimates in the literature.[47]

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

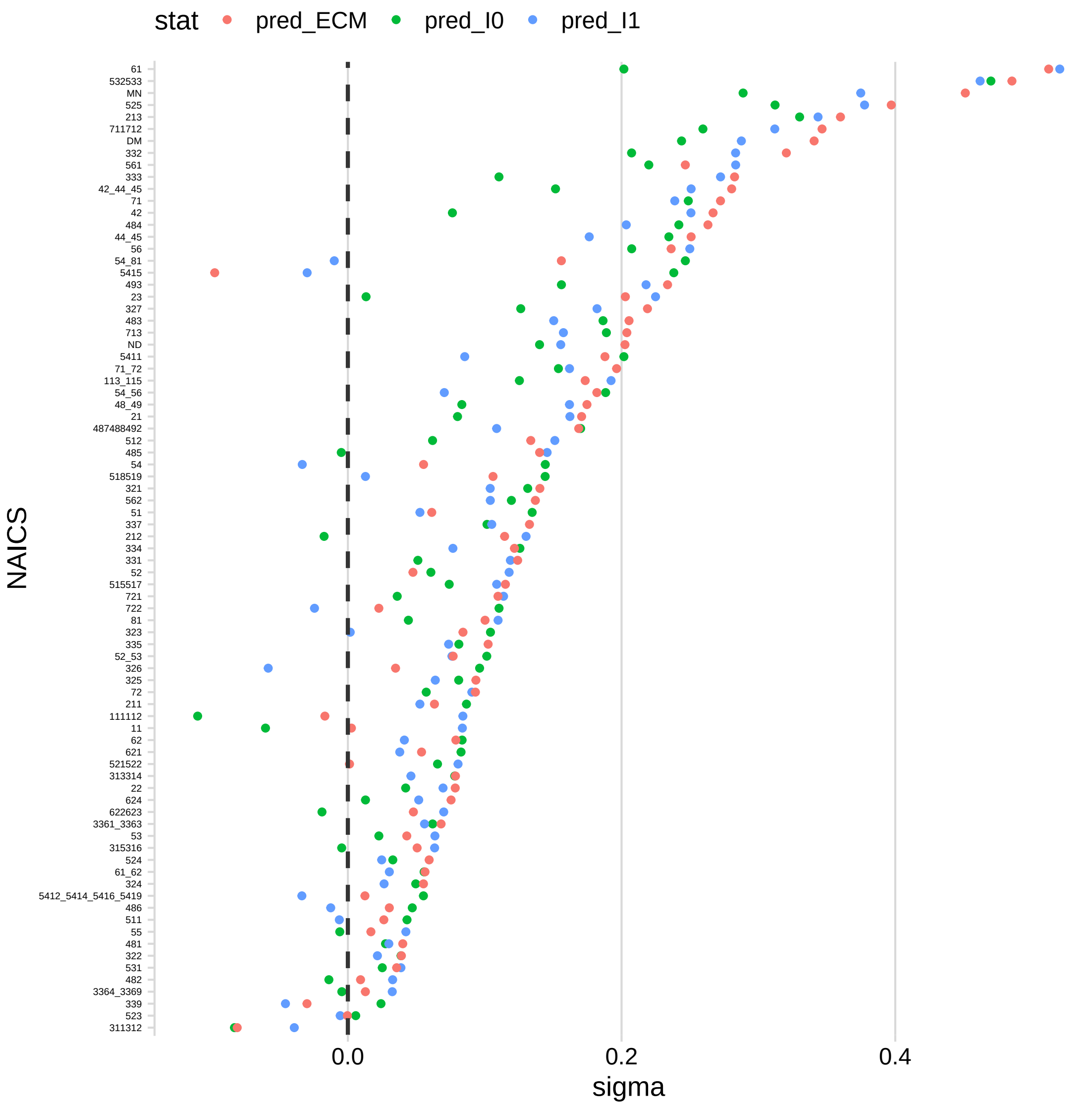
[47]One possible explanation may be that our sectors are very precisely defined (81). This is the hypothesis of Solow (1964, p. 118) who asserts that "[i]t seems plausible that, in general, elasticities of substitution should be smaller the more narrowly defined the industrial classification, and larger the degree of aggregation." cited in Young (2013). Although Young does not seem to find any empirical proof of it in his study.

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.[48]

Estimation of the elasticity of substitution Figure H.34 shows the estimates of the elasticity of substitution between capital and labour using the three specification from equations (42), (43) and (44).

Figure H.34: Sigma estimates



H.B.3 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 adjustment

[48] 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.

to prices variations. We assume fixed quantity of capital and labour consumed for each industry,

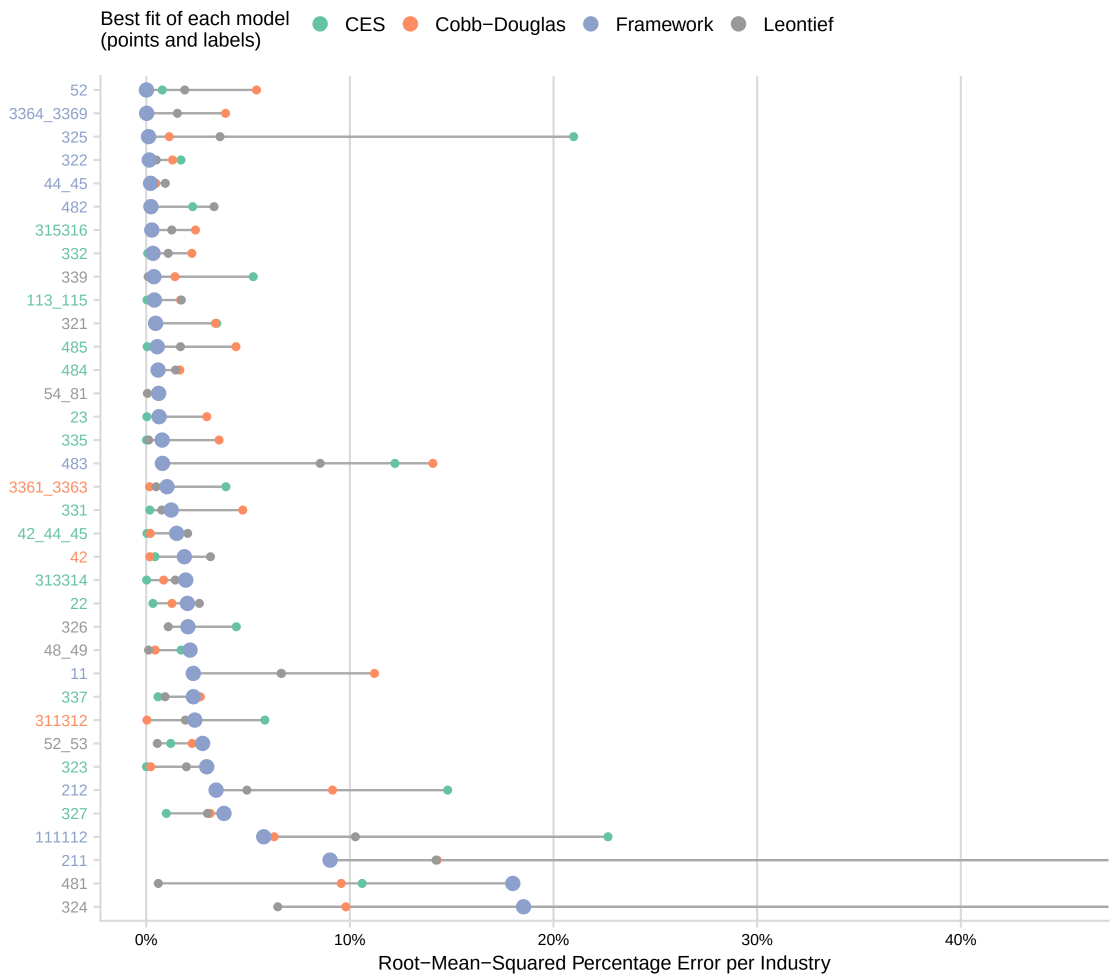
$$\begin{aligned} Y_1 &= r_1 K_0 + w_1 L_0 \\ \alpha_K &= \frac{r_1 K_0}{Y_1} \\ \alpha_L &= \frac{w_1 L_0}{Y_1} \end{aligned} \tag{46}$$

H.C 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 H.35 reproduces the trend of figure 16: our framework is better than all the others models for some industries, but more importantly, it is seldom out of touch.

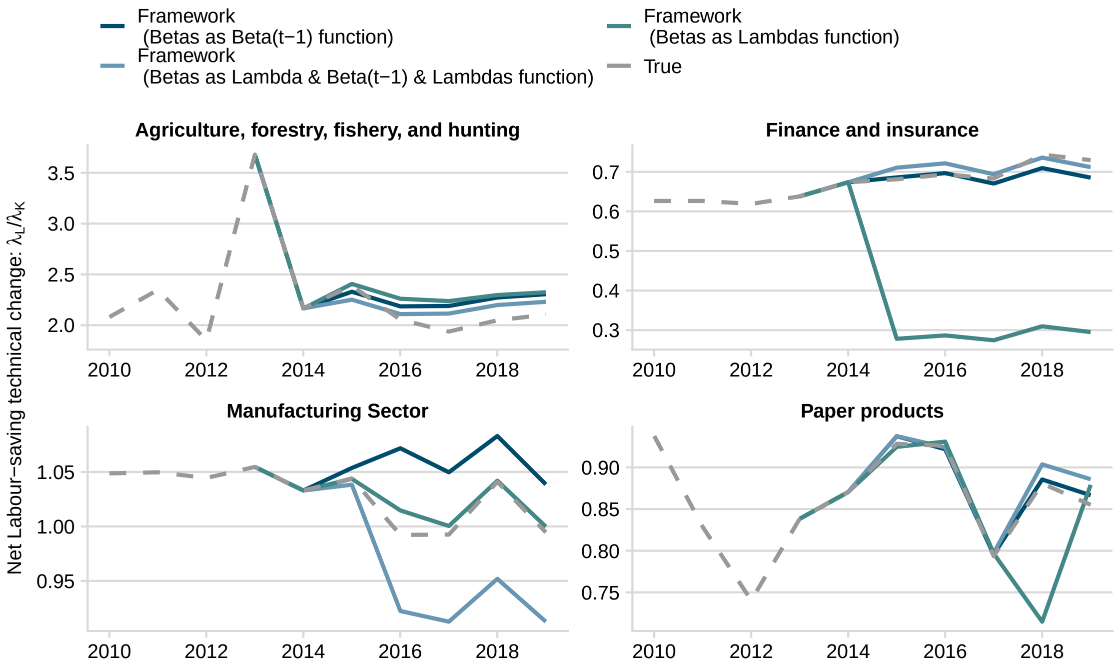
We have plotted the forecast of the bias of technical change for the four industries (Agriculture, Manufacturing, Finance and paper products) using the three specifications detailed in (40),(38),(39) (Figure H.36).

Figure H.35: 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.

Figure H.36: 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 (40) for the agricultural sector, equation (38) for the paper sector, equation (40) for the financial sector, and equation (39) for the manufacturing sector.

H.D Sensitivity to start year and length of the testing set

In this section, we present the results of the section 8.2 about the sensitivity of the forecasting power to the length of the training set and forecasting period.

Table H.29: 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 envelop	32%	35%	38%	36%	27%	37%	35%	27%	31%
Leontief	30%	25%	20%	26%	20%	17%	17%	22%	11%

Figure H.37: Forecast of labour share of the manufacturing sector with different length of the training versus testing set

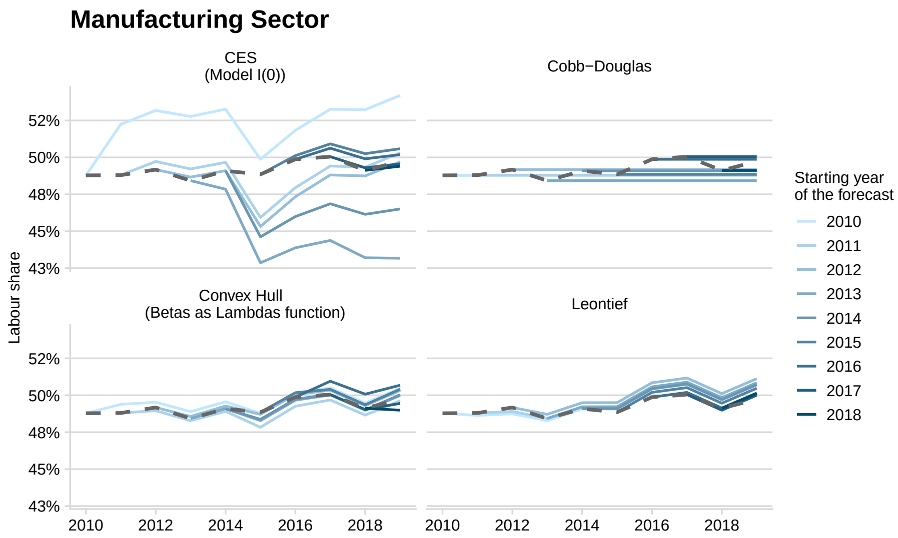


Table H.29 summarises the performance of the four models we consider with various starting year for the testing set. My framework has good performance across time. Let's notice that CES functions perform better on shorter periods of time (1 to 3 years). Two possible explanations are: i) they do not encapsulate 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 H.37, 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.[49]

My 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 8). 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.

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 H.38, H.37, H.39, H.40).

[49]Figures for Agriculture, Finance and Paper industry are available in appendix: Figures H.39,H.38,H.40.

Figure H.38: Forecast of labour share using our framework vs the true value (red) — with different length of the training versus testing set

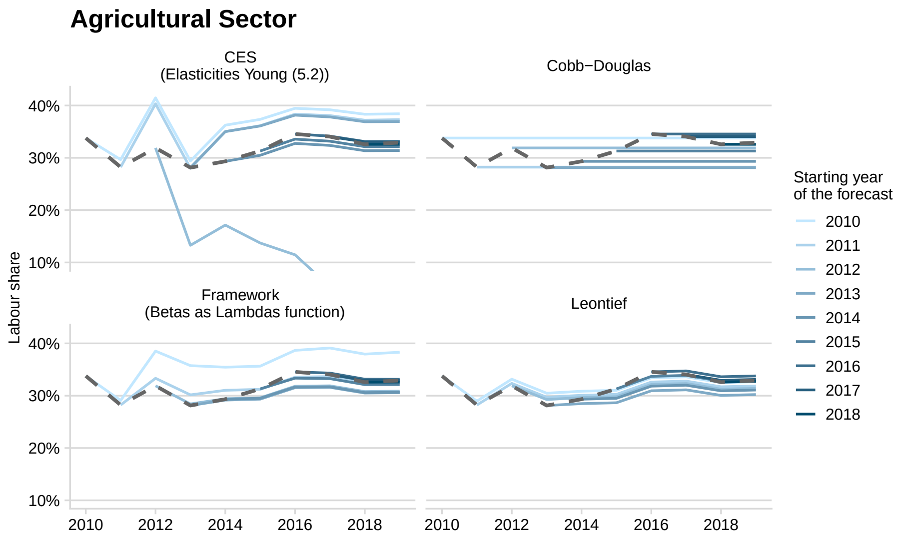


Figure H.39: Forecast of labour share using our framework vs the true value (red) — with different length of the training versus testing set

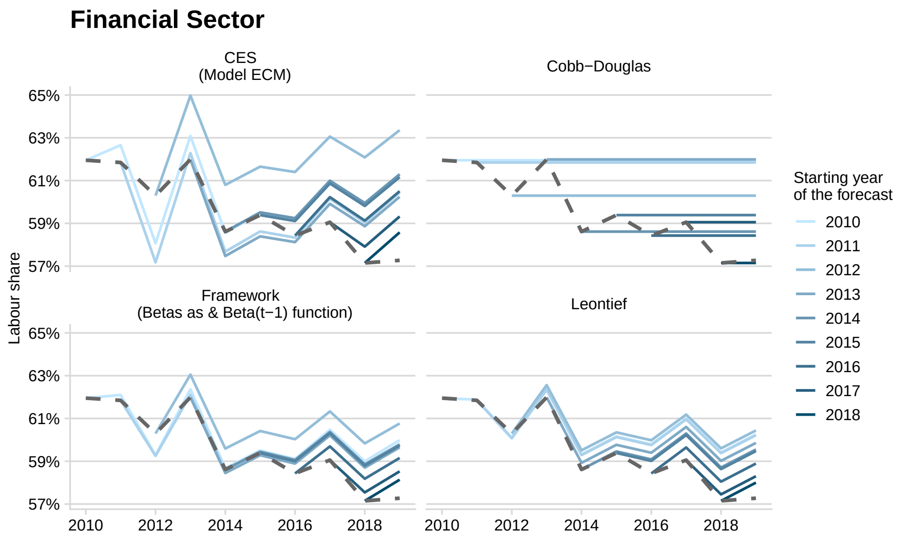
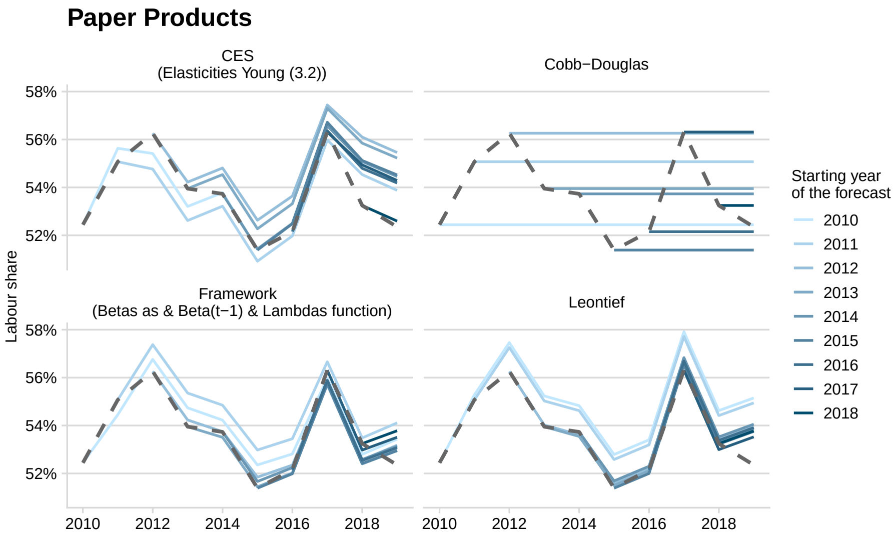


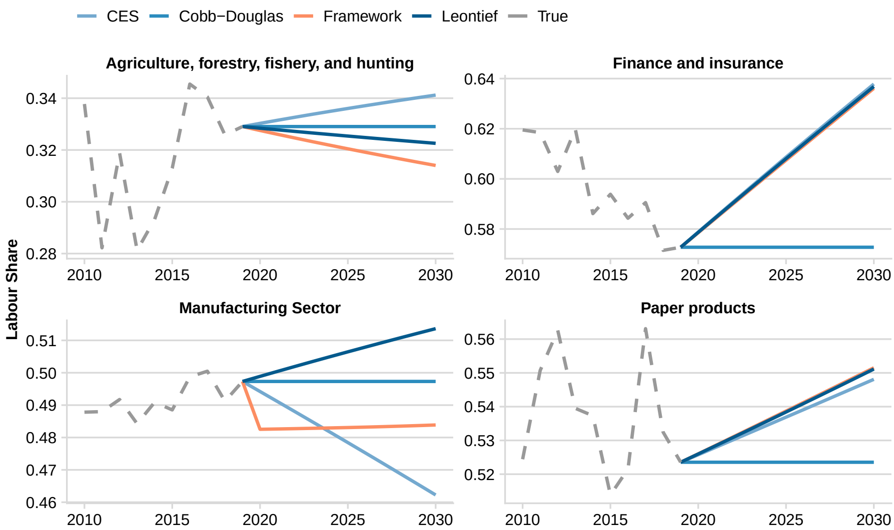
Figure H.40: Forecast of labour share using our framework vs the true value (red) — with different length of the training versus testing set



H.E Long-term 2030 Forecast

We use our framework to forecast the bias of technical change up to 2030 (Figure H.42), along with the forecast of the labour-share (Figure H.41 using the prices forecasted as in figure H.43).

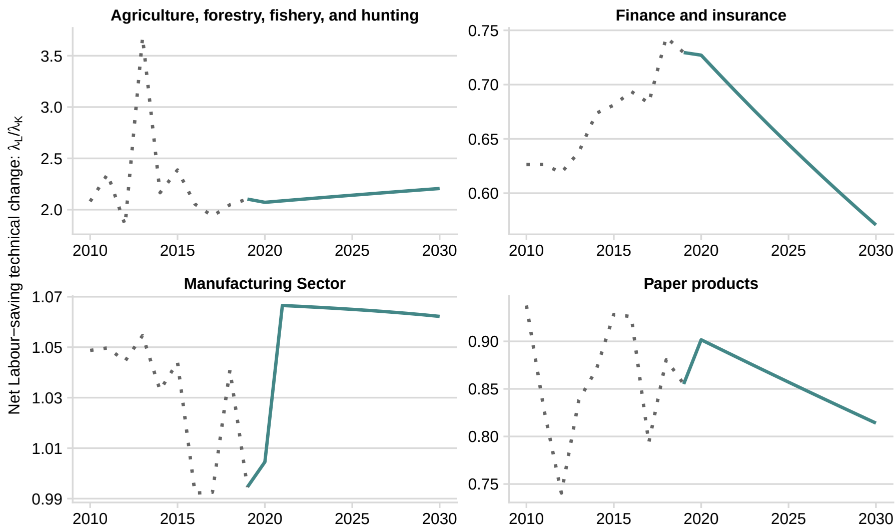
Figure H.41: Forecast of labour share up to 2030 for four industries



Note: The best specification over the period 2013-2019 of each model is retained.

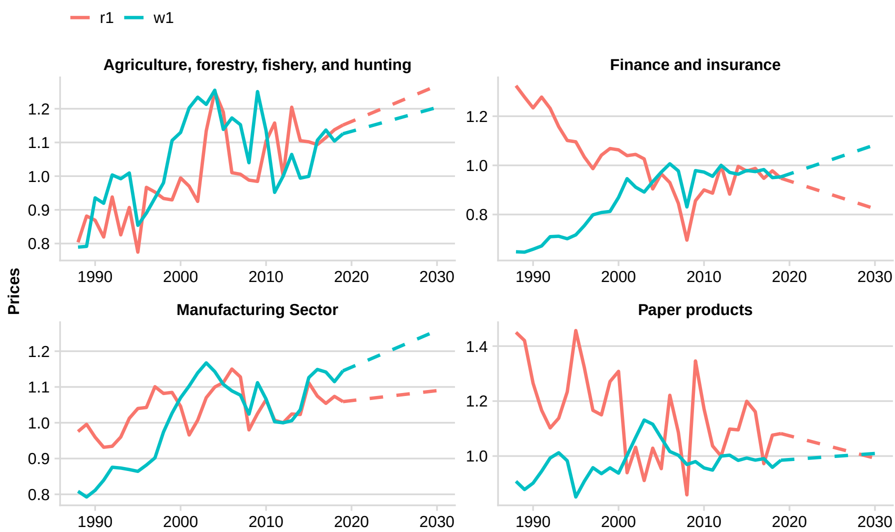
We assume that the prices of capital and labour follow a linear increase estimated on the 1987-2019 data (see Appendix H, Figure H.43). For the agricultural sector, our model predicts a decline in the labour share to just over 0.31, with a stable net labour-saving technical change (λ_L/λ_K) between 2 and 2.5, (see Figure H.42, Appendix H). The CES function predicts a slow increase in the labour share until 2030. My 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.

Figure H.42: Forecast of the bias of technical change up to 2030 for four industries



The best specification over the period 2013-2019 of our framework is retained.

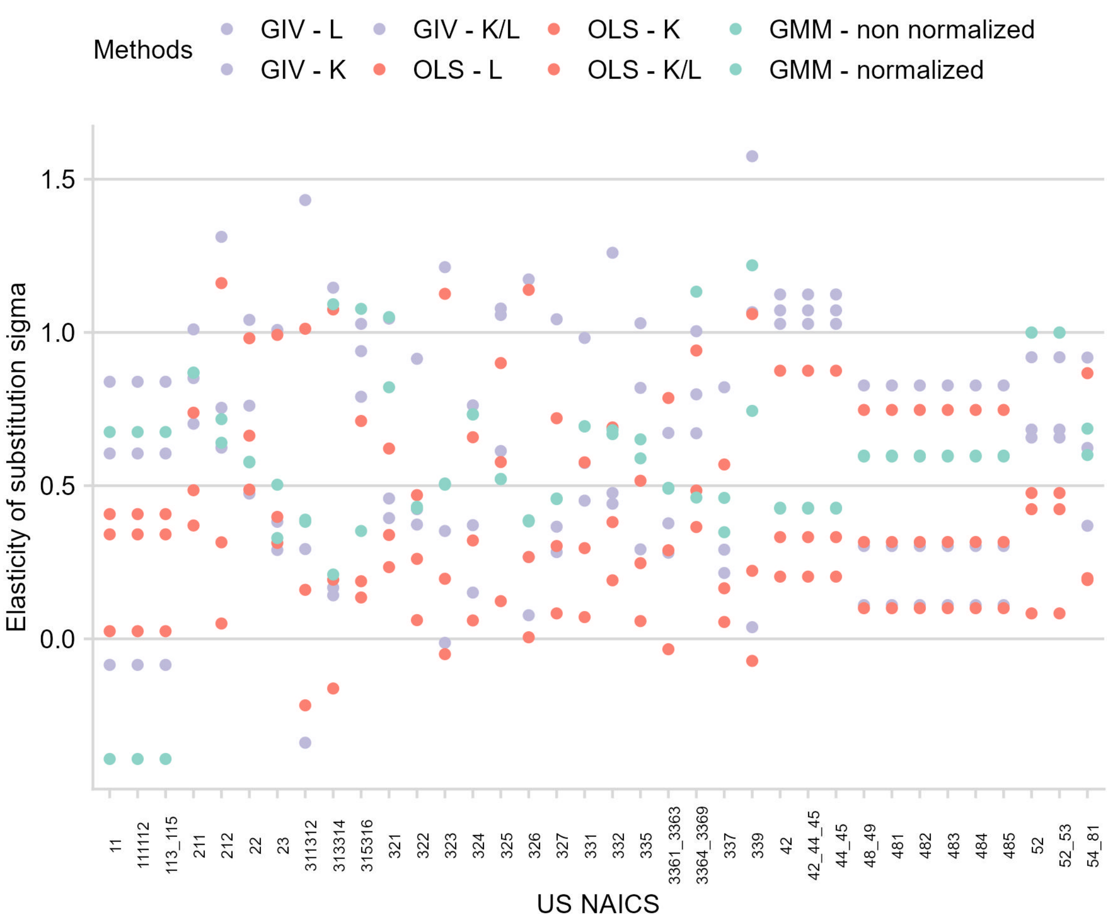
Figure H.43: Forecast of the prices of factors up to 2030 for four industries



Linear forecast based on estimate using 1987-2019 data.

I Young (2013) elasticities of substitution

Figure I.44: Estimates of the sector elasticities of substitution



Plot based on data from Young (2013), tables 3, 4 and 5.