# Capital Heterogeneity and the Decline of the Labour Share

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**Abstract**

We investigate the decline of the labour share in a world characterized by increasing heterogeneity of capital assets. Our results show that, over the 1970-2007 period, the decline of the labour share has been mainly driven by Information and Communication Technology (ICT) assets and is mitigated by increasing investments in R&D-based knowledge assets. Extending to other forms of intangible capital from 1995 onwards, we find that intangible investments related to innovation increase the labour share while those related to the organisation of firms contribute to its decline, particularly for the low and intermediate skilled workers. Our results are robust to an array of econometric issues, namely heterogeneity, cross-sectional dependence, and endogeneity.

**Keywords**: labour shares, technological change, ICT capital, intangible capital

**JEL Classification**: C23, E24, E25, O33

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# Introduction

There is considerable evidence that labour's share of GDP has been decreasing since the 1980s (Bentolila and Saint-Paul, 2003; Checchi and Garcia-Penalosa, 2010; Karabarbounis and Neiman, 2014). Reasons for the labour share decline include market regulations (Azmat *et al.*, 2012), globalization (Elsby *et al.*, 2013), measurement issues (Koh *et al.*, 2020), technological change (Bassanini and Manfredi, 2012), and market concentration (Autor *et al.*, 2017). Over time, there has also been an increasing recognition of the importance of identifying the drivers of the capital share (see Piketty and Zucman, 2014), in order to understand the overall allocation of income among factor inputs. However, in most analyses, capital's share is based on the residual between nominal value added and payments to labour input. This implies that the capital share can include excess rents (Autor *et al.*, 2020, Barkai, 2020), mis-allocation of the labour income of the self-employed or, of most importance from the perspective of this paper, returns to unmeasured intangible capital.

Relatedly, most of the discussion on the decline of the labour share has considered a single capital asset, which can either substitute or complement labour. One of the main arguments is that advances in information and communication technologies have reduced the price of capital while simultaneously increasing the degree to which capital can substitute workers' tasks, leading to more capital-intensive production (Karabarbounis and Neiman, 2014). In contrast, Lawrence (2015) claims that rapid labour augmenting technical change has led to a decline of the effective capital labour ratio, and given the complementarity between capital and labour, has decreased the labour share. Both approaches ignore the possibility that capital and labour can be substitutes or complements depending on the asset type. In this paper we address the issue of capital heterogeneity and provide new evidence on its role in driving movements in the labour share.

To guide our empirical analysis, we first develop a theoretical (multi-sector) framework where variations in the aggregate labour share are explained by the elasticity of substitution of different types of capital assets (within effect) and changes in the economy's structure (between effect) induced by the increase in the capital-to-income ratio. We then assess empirically the predictions of the model by performing a two-fold regression analysis using a large industry dataset for OECD countries. First, we carry out a long-run analysis covering the 1970-2007 period. To account for capital heterogeneity, we rely on a division into ICT and non-ICT capital, and then include a measure of knowledge capital, traditionally proxied by R&D capital. Our estimation procedure fully exploits the longitudinal and time-series variation of the data, by estimating an Error Correction Model (ECM) and controlling for parameter heterogeneity and cross-sectional dependence (Eberhardt *et al.*, 2013). This dynamic specification has been shown to produce consistent estimates even in the presence of simultaneity (Pesaran and Shin, 1999). In addition, the inclusion of controls for cross-sectional dependence can account for the effect of unobserved factors which create inter-dependencies across industries and countries, such as globalization or spillover effects (Eberhardt and Presbitero, 2015,Chudik *et al.*, 2011). This further addresses endogenity issues due to omitted variables (Eberhardt and Teal, 2020, Lenkei *et al.*, 2018).

Second, we focus on the determinants of the labour share for a relatively shorter period (1995-2007) using new data on intangible assets, (Niebel *et al.*, 2016), based on the pioneering approach of Corrado *et al.* (2005, and 2009). Intangibles include R&D and other innovative activities, overall termed innovative property investment, and economic competencies, which cover investments in organizational changes, workforce training and brand development. Given that the new dataset is only available for a short period, our estimation relies on a static fixed-effects framework and on an identification strategy to address endogeneity issues. Our instruments are based on indicators of services markets regulation, under the assumption that firms' decisions to invest in specific capital types depends on the regulatory setting underlying the functioning of input markets.

Our results show that the different types of capital assets drive the labour share in different directions. In the long run estimates, ICT capital plays a major role in driving the decline in the labour share, but with heterogeneous impacts, particularly across industries. For example, ICT is a more important explanatory factor in electronic equipment manufacturing and less so in services such as hotels and catering. In contrast, R&D appears to raise the labour share as these activities create rents that are likely shared by all workers (Aghion *et al.*, 2019b).

Using new estimates of intangible capital, in the second part of our analysis, we find that economic competencies, together with ICT, have a negative impact on the labour share, particularly among low and intermediate skilled workers. Innovative properties, on the other hand, mainly have a positive effect. Out-of-sample predictions show that our empirical model fits well the actual movements in the labour share in the latest years. Overall, our study concludes that the type of capital assets matters and accounting for capital heterogeneity is crucial to understand changes in the labour share.

This paper contributes to several important strands of the literature. We contribute to the debate on the drivers of the labour share dynamics stressing how this pattern is affected by the firms' increasing investments in new capital types. Specifically, our work complements the analysis by Koh *et al.* (2020) to a cross-country, cross-industry setting, showing that intangibles explain an important part of changes in the labour share. However, the effect of intangibles varies with the nature of the investment (innovative properties vs economic competencies) and in relation to the complementarity between these assets and other inputs (ICT capital and skilled labour). Our work also extends the analysis of intangible capital to the distribution of factor returns, a topic that has remained largely unexplored in this recent literature, which has instead focused on measurement issues, productivity effects and spillovers from intangibles (Corrado *et al.*, 2017). The model we develop also offers some insights on the role of capital deepening on structural change (Acemoglu and Guerrieri, 2008). In fact, we show that the capital-output ratio affects not only industries' labour share but also the relative importance of each sector in the economy.

The remainder of the paper is organised as follows. Section I briefly reviews the relevant literature. Section II sets out the theoretical framework. Section III discusses our empirical specification, the data set used for the estimation of the ECM and presents our first set of results. Section IV presents the the analysis using the extended forms of intangible assets and assesses their impact on the decline of the labour share. Finally, Section V concludes the paper.

# I Background

The decline of the labour share is global (Dao *et al.*, 2019) and has been documented for the US (Elsby *et al.*, 2013), for other developed countries (O'Mahony *et al.*, 2019, Fukao and Perugini, 2020), European transition countries (Rincon-Aznar *et al.*, 2015) and emerging economies (Luo and Zhang, 2010; Bai and Qian, 2010). Understanding what drives this decline has been the subject of much analysis by economists in recent years. Earlier studies focused on the role of product and labour market reforms, following the adoption of liberalisation and privatisation programmes in many OECD countries in an attempt to increase productivity. Findings in relation to the labour share differ across studies. While increasing competition is generally associated with increasing labour shares (Bassanini and Manfredi, 2012), Azmat *et al.* (2012) show that the privatisation of network services is associated with a reduction in the labour share, as the focus of managers shifts away from employment targets and towards profitability targets. In the labour market, Blanchard and Giavazzi (2003) develop a model where the decline of the labour share is a short-run phenomenon led by a decrease in the bargaining power of unions. Their model predicts that the labour share increases in the long-run, due to the interaction between product and labour market regulations. However, no such increase is apparent in the data. Recent evidence shows that labour market reforms that weaken labour protection are positively correlated with the labour share's decline (Ciminelli *et al.*, 2018), whilst policies promoting workers' reallocation are likely to increase the labour share (Pak and Schwellnus, 2019).

Theoretically, assessing the impact of market regulations is complex because different types of policies may be interdependent and interactions between labour and product market regulations need to be carefully modelled (Fiori *et al.*, 2012). Empirically, institutional settings do not present large variations over time and hence their impact tends to be captured by the idiosyncratic component of empirical models, such as country- and/or time-specific fixed effects. Therefore, the effect of regulations on the labour share remains unknown. O'Mahony *et al.* (2019) show that the downward trend of the labour share is very persistent across countries with different institutional frameworks. This suggests that institutions may not be primarily responsible for the decline in the labour share. However, if certain institutions have changed in a similar way across countries, as has been the case for union bargaining power, these results do not preclude a similar impact on the labour share.

A popular explanation in the earlier literature was that globalisation has moved job opportunities to low wage countries leading to a downward pressure on wages in advanced economies. Elsby *et al.* (2013) provide empirical support for this hypothesis as they find a strong association between the decline of the labour share and increased import competition in the US. Conversely, Haskel *et al.* (2012) show that US wages are not strongly related to US imports from emerging economies, which weakens the prediction of a negative relationship between globalisation and the labour share. Similarly, Autor *et al.* (2017) document that the decline of the labour share has been observed in both traded and non-traded goods sectors, implying that the impact of trade is not as relevant as others have argued. Young and Tackett (2018) extend this analysis by considering social and political globalisation next to the standard measures of trade flows. Their results show that, while economic globalisation is negatively associated with the labour share, promoting greater movement of individuals, ideas and information contribute to its increase. However, the size of the estimated effects is rather small and not always significant.

The role of technical change has also received prominent support in the literature. Recent technologies have increasingly led to more capital-intensive production. This trend has been facilitated by a decrease in the price of capital goods, leading to higher substitution of labour by capital (Bentolila and Saint-Paul, 2003; Karabarbounis and Neiman, 2014). Investments in ICT, automation and artificial intelligence are gradually replacing routine tasks previously performed by workers (Acemoglu and Restrepo, 2017, and 2018), changing the structure of the workplace and further reducing the demand for workers, particularly those with low skills. In addition, vom Lehn (2018) documents that, in the US, the decline in the labour share has spread to high skilled occupations characterized by significant amounts of routine work, especially after 2000.

Technological progress may have also contributed to the decline of the labour share via a more subtle channel, as the adoption and diffusion of digital technologies has strengthened network effects, facilitating the rise of dominant 'superstar' firms (Autor *et al.*, 2020), characterized by above average productivity, high mark-ups and low labour share. Aghion *et al.* (2019c) propose a theoretical framework consistent with these observations, where ICT allows high productivity firms to expand into multiple markets, contributing to the increase in aggregate mark-up and the reduction in aggregate labour share. The focus on market power and rising profits is supported by empirical evidence in Dixon and Lim (2018) and in Barkai (2020), who highlight the decline in both the labour share and the capital share, while a larger among of output is being distributed as profits. However, additional 'profits' might also represent returns to unmeasured inputs, in particular intangible assets, which are likely to be large in the so called 'superstar' firms. De Ridder (2019) supports this claim by relating intangibles-intensive firms with higher markups and lower labour share.

A related research effort focuses on the measurement of factor inputs and their corresponding labour share. For instance, Koh *et al.* (2020) claim that capitalisation of intellectual property products (IPP) in national accounts may help to explain a large portion of the labour share's decline in the United States. Cho *et al.* (2017) contend that the fall in the labour share is due to increased capital depreciation, and the share of labour in net national income shows little decline. Del Rio and Lores (2019) argue that a decline in capital efficiency and a fall in capital relative prices are the major factors responsible for the downward trend in the US labour share.

Both the literature on market power and on defining capital input have brought to the fore the need to focus on capital's share in its own right rather than just looking at labour's share. However, the definition of capital used in many studies generally refers to a total capital measure, without accounting for the possibility that different types of assets can drive the labour share in opposing directions, as some may substitute, and others may complement workers. For example, investments in ICT have often gone hand-in-hand with investment in complementary assets, such as organizational changes, leading to more efficient productions and higher productivity (Pieri *et al.*, 2018 Bertschek and Kaiser, 2004 Black and Lynch, 2001). In addition, the diffusion of ICT has often resulted in the substitution of tasks performed by low and intermediate skilled workers, who have experienced a decline in employment levels and wages (Bresnahan *et al.*, 2002 Michaels *et al.*, 2014). Hence, ICT and complementary intangible assets are likely to have contributed to the decline of the labour share.

On the other hand, the impact of innovative assets can be radically different. There is an extensive literature relating changes in firms' performance to worker compensation, which implies that part of the gains from increased productivity/profits are shared between the firm and its employees (Card *et al.*, 2016). Overall, there has been a decline in rent sharing over time in several OECD countries (Bell *et al.*, 2018).[1] However, a related literature shows that rent-sharing is still strong among innovative firms, even in countries characterized by highly flexible labour markets regulations, like the US and the UK, with few constraints on the hiring and firing of workers (Van Reenen, 1996, Kline *et al.*, 2019). Innovation activities largely rely on highly skilled labour (researchers and scientists). These workers have specific knowledge and creativity and are hard to replace, as companies will lose some of their investments in specific human capital (Oi, 1962, Hart and Malley, 1996, Vecchi, 2000). The imperfect substitutability of incumbent workers with new hires provides an opportunity for rent sharing. Kline *et al.* (2019) document that rent sharing increases following an innovation (patent) shock, and the response is larger among workers in the top half of the earnings distribution.[2] This suggests that investments in innovative assets might be complementary to labour, particularly to high-skilled workers. Aghion *et al.* (2019b) show that this complementarity might also extend to low-skilled workers in high-tech companies, as the wage premium associated with being employed in R&D-intensive firms for these workers is positive and even greater than the wage premium for the highly skilled. It is therefore possible that the positive effect of innovative activities on the labour share extends to different types of workers.

Despite the widespread diffusion of ICT and intangible assets across firms and industries, and the substantial improvements in their economic measurement, little is known about the effect of heterogeneous capital on the labour share. Recent work has highlighted how the increasing role of ICT and complementary intangible capital has been crucial in promoting productivity growth (Corrado *et al.*, 2017 Niebel *et al.*, 2016), increasing investment demand (Alesina *et al.*, 2005; Cette *et al.*, 2017) and in affecting the long-run capital-income ratio (Madsen *et al.*, 2020). This highlights the importance of also accounting for the role of different types of capital in understanding the dynamics of the labour share. This is the main objective of this paper.

## II Theoretical Framework

In this section we develop a theoretical set-up which we use as guidance in the interpretation of our econometric results. Let us consider a static, multi-sector economy with aggregate output, $Y$, defined as a Constant Elasticity of Substitution (CES) combination of industry outputs.

There are two sectors in this economy, denoted by subscripts $I$ and $N$ ($i = I, N$), combining capital assets and labour inputs of different types, $K_i$ and $L_i$. We could think of one sector as innovative ($I$), using R&D-based knowledge capital and high skilled labour. The other is a more traditional industry ($N$), and uses assets such as machinery and equipment, and low skilled labour ($N$). Aggregate output is (time subscript omitted for simplicity):

$$Y = [\phi_I Y_I^{-\epsilon} + \phi_N Y_N^{-\epsilon}]^{-\frac{1}{\epsilon}}. \tag{1}$$

$\phi_i$ is a distribution parameter with $0 < \phi_i < 1$ and $\sum_i \phi_i = 1$, whilst $\epsilon$ is a substitution parameter between goods ($\epsilon > -\infty$). The elasticity of substitution is defined as $\vartheta = 1/(1+\epsilon)$. These goods are gross substitutes if $\vartheta > 1$ (or $\epsilon < 0$) and complements if $\vartheta < 1$ (or $\epsilon > 0$). Assuming perfectly competitive markets, the (relative) demand of each intermediate good is

$$\frac{Y_i}{Y} = \phi_i^{\frac{1}{1+\epsilon}} (\frac{P_i}{P})^{-\frac{1}{1+\epsilon}}, \tag{2}$$

in which $P_i$ is the industry output price and $P$ is the price of aggregate output.

Each sector produces with a CES technology with factor-specific technical change ($A_{Li} > 0$ and $A_{Ki} > 0$):

$$Y_i = [\alpha_i (A_{Li} L_i)^{-\sigma_i} + (1-\alpha_i)(A_{Ki} K_i)^{-\sigma_i}]^{-\frac{1}{\sigma_i}}, \tag{3}$$

where $Y_i$ is real output, $L_i$ is the number of employees, $K_i$ the capital stock. $\eta_i = 1/(1+\sigma_i)$ is the elasticity of substitution between factors used in each production, and $\sigma_i$ is the corresponding substitution parameter. In each sector, the labour share of output is defined as the proportion of value added accruing to workers, $S_i^L = \frac{W_i L_i}{p_i Y_i}$, where $W_i$ is the wage rate. Under the assumption of constant returns to scale ($0 < \alpha_i < 1$), the industry labour share can be derived from the capital share on income, $S_i^L = 1 - S_i^K = 1 - (R_i K_i / p_i Y_i)$, where $R_i$ is the user cost of industry capital. If we define the capital-to-output ratio in a given industry as $\tilde{k}_i = K_i / Y_i$, and following

Bentolila and Saint-Paul (2003), the labour share of industry output can be expressed as:

$$S_i^L = 1 - \underbrace{(1-\alpha_i)(A_{Ki}\tilde{k}_i)_i^{-\sigma_i}}_{S_i^K}. \tag{4}$$

Therefore, it is easy to show that an increase in the capital-to-output ratio, $\tilde{k}_i$, generates a change in $S_i^L$ depending on the substitution parameter between capital and labour at industry level ($\sigma_i$):

$$\frac{\partial S_i^L}{\partial \tilde{k}_i} = \sigma_i(1-\alpha_i)A_{Ki}^{-\sigma_i}\tilde{k}^{-\sigma_i-1}. \tag{5}$$

If factor inputs are gross substitutes at industry level ($\sigma_i < 0$ or equivalently $\eta_i > 1$) then we have $\frac{\partial S_i^L}{\partial \tilde{k}_i} < 0$ , whilst if they are gross complements then $\frac{\partial S_i^L}{\partial \tilde{k}_i} > 0$ ($\sigma_i > 0$ or $\eta_i < 1$).

At the aggregate level, the labour share is a weighted average of industry labour shares, in which the industry shares are defined as the ratio between the value of industry and total output, $\theta_i = P_iY_i/(\sum_i P_iY_i)$:

$$S^L = \frac{\sum_i W_iL_i}{PY} = S_I^L\theta_I + S_N^L\theta_N. \tag{6}$$

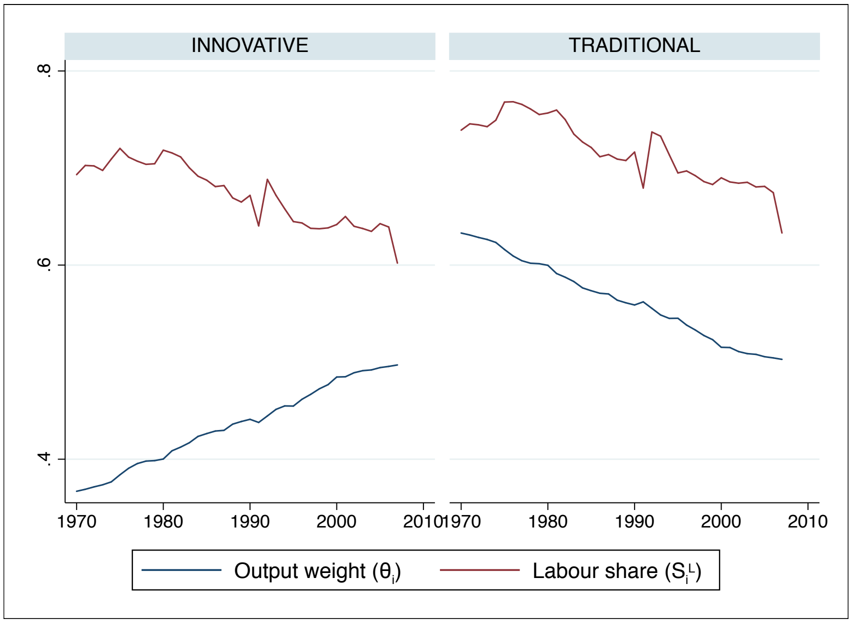
As a consequence, when an industry increases its capital-output ratio the effect on the economy-wide labour share is a combination of two effects, *within* and *between* (Karabarbounis and Neiman, 2014):[3]

$$\frac{\partial S^L}{\partial \tilde{k}_I} = \underbrace{\frac{\partial S_I^L}{\partial \tilde{k}_I}\theta_I}_{within-effect} + \underbrace{\frac{\partial \theta_I}{\partial \tilde{k}_I}(S_I^L - S_N^L)}_{between-effect}. \tag{7}$$

The former is a first-order effect reflecting the change of the industry labour share, $S_I^L$, and is proportional to the relative size of the industry, $\theta_I$ (*within effect*). The latter is a second-order effect and captures the structural change induced by the increase in the capital-output ratio, i.e. the re-allocation of the economy's resources towards (or away from) industries with a lower (or higher) labour share (see Acemoglu and Guerrieri, 2008). This effect reflects the change in the industry relative size and the gap in the sectoral labour shares (*between effect*). The within-effect is negligible when the industry share in GDP, $\theta_I$, tends to zero, whilst the between-effect is irrelevant when the labour share is equal among sectors.

To gain insights on the sectoral sources of the labour share dynamics at an aggregate level, Figure 1 plots the

Figure 1: Industry labour share and output weights: Innovative vs Traditional industries (un-weighted mean)




**Notes:** Output weight ($\theta_i$) is the ratio between the industry group value added and total value added. Labour share ($S_i^L$) is the ratio between labour compensation and value added at industry level. Innovative industries (cat. ISIC Rev. 3): 24, 30t33, 34t35, 60t63, 64, 65t67, 71t74. Traditional industries: 15t16, 17t19, 20, 21t22, 36t37, 40t41, 45 50t52, 55, 90t93. Country list: Austria (AT); Australia (AUS); Belgium (BE); Czech Republic (CZ); Denmark (DK); France (FR); Finland (FI); Germany (DE); Hungary (HU); Ireland (IE); Italy (IT); Japan (JP); Netherlands (NL); Spain (ES); Sweden (SE); United Kingdom (UK); United States (US).

evolution of the labour share and the share of industry output in GDP for innovative and traditional sectors, for our sample of OECD countries (see Sections III.1 and IV for details). The group of innovative industries includes high-tech manufacturing sectors and knowledge intensive services, based on a Eurostat classification,[4] whilst the group of traditional industries collects all remaining sectors. Figure 1 shows that innovative industries are more capital intensive and have a lower labour share compared to traditional sectors ($S_I^L - S_N^L < 0$). Furthermore, the GDP share of innovative industries is increasing over time (primarily due to the expansion of high-tech services).

Based on this evidence, we characterize how the aggregate labour share should change as a result of capital deepening in the light of our model's predictions (see Appendix Table A.1). As eqs. (5) and (7) show, the within-effect varies with the factor elasticity of substitution: if factors are complements (substitutes) $\sigma_i > 0$ ($\sigma_i < 0$), the within-effect is positive (negative). Conversely, the between-effect depends on the sign and the size of the substitution and distribution parameters ($\epsilon, \phi_I$). To show this, we re-formulate the industry share, $\theta_I$, as a function of the real output ratio by exploiting the inverse of eq. (2):

$$\theta_I = \frac{P_I}{P} \times \frac{Y_I}{Y} = \phi_I \times \big(\frac{Y_I}{Y}\big)^{-\epsilon}. \tag{8}$$

The response of $\theta_I$ to an increase in $\tilde{k}_I$ is positive when $\epsilon < 0$. When $\epsilon > 0$, $\partial\theta_I/\partial\tilde{k}_I$ is positive only if the real output ratio $Y_I/Y$ is lower than the threshold $\phi^{1/\epsilon}$; otherwise, the partial derivative, $\partial\theta_I/\partial\tilde{k}_I$, is negative. In economic terms, these findings can be rationalised as follows. When goods are *substitutes* ($\epsilon < 0$) or *weak complements* ($\epsilon > 0$ but with low values), $\theta_I$ increases with $\tilde{k}_I$.[5] Conversely, when goods are *strong complements* ($\epsilon > 0$ with large values), the increase in $Y_I$ is accompanied by a rise in the relative price, reducing the share of the sector in GDP.[6]

Extending this model to multiple sectors would make the framework less tractable. However, we can think of the economy as made up of many broad sectors or industries, consisting of sub-industries that specialise in types of capital used. The impact on the average labour share then depends on the relative magnitudes of the between- and within- effects in each broad sector. Our modeling framework allows for the possibility that some capital inputs may substitute and others may complement labour. This is consistent with our discussion in the Background Section, where we argue that various forms of capital affect the labour share in different directions. We can summarize these predictions in the following two hypotheses:

*H1*: *Non-ICT capital, together with ICT and complementary intangible assets, substitute labour, hence their increase leads to a decrease in the labour share*;

*H2*: *Innovative capital, such as R&D-based knowledge assets, complement labour, hence their increase leads to an increase in the labour share.*

# III The long-run impact of technology and capital

## III.1 Empirical specification and data

In the empirical analysis, we estimate a stochastic version of the industry labour share (eq. 4), expressed in logs, using panel data for an industry-by-country sample:

$$\ln S^L_{ijt} = \alpha_{0ij} + \alpha_{1ij} \ln \tilde{k}_{ijt} + \alpha_{2ij} \ln A_{ijt} + \epsilon_{ijt}, \tag{9}$$

where $\tilde{k}$ is the capital-output ratio and $A$ is capital-specific technical change. Subscript $i$ denotes industries and $j$ countries, $\alpha_{0ij}$ are industry-country fixed effects and $\epsilon_{ijt}$ is a spherical error term. If labour and capital are gross substitutes the coefficient of capital intensity is expected to be negative ($\alpha_2 < 0$), and positive if factor inputs are complements ($\alpha_2 > 0$). $A$ is not observable but can be proxied by Total Factor Productivity (TFP), as is common in the existing literature. The sign of the TFP parameter should mirror that of the capital-to-output ratio (Bassanini and Manfredi, 2012; Karabarbounis and Neiman, 2014). The use of TFP as a proxy for technical change presents some caveats, as it can capture other unmeasured factors, such as institutions (Mankiw *et al.*, 1992), management practices (Bloom *et al.*, 2016), spillover and measurement errors (Griliches, 1998), which can affect movements in the labour share, beyond technical change. The inclusion of controls for cross sectional dependence in our analysis captures the role of unobserved common factors that can create dependency across units, hence it partially addresses this problem (Eberhardt and Teal, 2020). Nevertheless, estimates of the TFP coefficient should be interpreted with caution.

The coefficients of eq. (9) represent long-run elasticities. Empirically, these can be identified by rewriting a dynamic version of the labour share equation using an autoregressive distributed lag process, ARDL($p$,$q$) which here, for notational simplicity, is formulated with a lag order of one:

$$\ln S^L_{ijt} = \beta_{0ij} + \beta_{1ij} \ln S^L_{ijt-1} + \beta_{2ij} \ln \tilde{k}_{ijt} + \beta_{3ij} \ln \tilde{k}_{ijt-1} + \beta_{4ij} \ln A_{ijt} + \beta_{5ij} \ln A_{ijt-1} + \epsilon_{ijt}. \tag{10}$$

This can be reformulated as an error correction mechanism (ECM), as follows:

$$\Delta \ln S^L_{ijt} = \gamma_{0ij} + \gamma_{1ij} \Delta \ln \tilde{k}_{ijt} + \gamma_{2ij} \Delta \ln A_{ijt} + \gamma_{3ij} \ln S^L_{ijt-1} + \gamma_{4ij} \ln \tilde{k}_{ijt-1} + \gamma_{5ij} \ln A_{ijt-1} + \epsilon_{ijt}. \tag{11}$$

Equation (11) represents our benchmark specification and can be used to estimate long-run effects. For instance, for capital intensity, the long-run parameter is defined as: $\alpha_{1ij} = -\gamma_{4ij}/\gamma_{3ij}$, whose significance is checked using the non-linear test of the delta method. The coefficient $\gamma_{3ij}$ indicates the speed at which the economy returns to its long-run equilibrium. Inference on this parameter will provide insights into the presence of a long-run equilibrium relationship. This coefficient is expected to be significant and negatively signed when such long-run cointegrating relationship exists. Equation (11) is then extended by including different types of capital assets, starting with the distinction between ICT and non-ICT capital and further expanding our specification to account for the impact of R&D-based knowledge capital. As we discuss in detail below, our main estimates account for parameter heterogeneity and each coefficient is estimated at the level of single industry-by-country unit, $ij$.

We estimate equation (11) using data from the EU KLEMS dataset (release 2009). This data set covers seventeen OECD countries and twenty industries (12 manufacturing and 8 service industries), spanning from 1970 to 2007.[7] The EU KLEMS dataset provides information on industry accounts (labour compensation, value added, capital services with a division into ICT and non-ICT components) and derived variables such as TFP. Labour compensation includes non-wage labour costs, such as employers' contributions to pensions. ICT capital includes computer hardware, communications equipment and software. Non-ICT capital includes other plant and equipment, transport equipment, structures and other assets that were part of the national accounts at that time (see O'Mahony and Timmer, 2009 and our Appendix A for details). Our release of EU KLEMS does not include Research and Development investment which was added to the national accounts with the 2008 revision of the System of National Accounts, SNA (Ker and Galindo-Rueda, 2017). We take data on R&D expenditure from OECD ANBERD 2002 and 2006, and build a measure of R&D capital stock with the same methodology used by EU KLEMS for capital inputs. All measures of capital inputs are divided by industry value added. Appendix Table A.2 and A.3 present summary statistics at the country and industry level.

The version of EU KLEMS used in our analysis offers a twofold advantage compared to alternative sources or the newer releases of the dataset. First, the time period is long enough to cover both the uptake of ICT and intangible investments while excluding the years after the financial turmoil of 2008-09, thus enabling the identification of the long-run impact of new capital inputs net of the effect of the Great Recession. Second, data on labour input by skill types are available for a larger set of countries/industries and a longer time span.

The use of industry data is particularly suitable to test the hypotheses that arise from our sector-based theoretical model. Industry data have the advantage of measuring outputs and inputs according to national accounting conventions derived from economic theory. This is especially the case for capital inputs, which are the focus of this paper. Industry data also allow us to quantify capital services rather than capital stocks and to calculate comprehensive measures that include all tangible and intangible assets within a coherent framework. The main disadvantage of industry compared to firm level data is that, being aggregates, they cannot pick up micro influences such as the impact of superstar firms. However, firm level data rarely include sufficient information to accurately measure capital services. Hence, we see industry and firm sources as complementary – each source provides information that the other cannot.

### III.2 Baseline results

Table 1 presents the results for our baseline specification, reporting estimates for the long-run coefficients and the error correction term, assuming a one year lag structure, ARDL(1,1).[8] In the first column of Table 1, we present estimates based on a fixed effect estimator, where coefficients are imposed to be common for all cross-sectional units (industry-by-country) in our data. In columns (2) through (6) we relax this assumption and present estimates based on an Augmented Mean Group (AMG) estimator (Eberhardt and Bond, 2018). This procedure estimates the specification separately for each panel unit, controlling for the presence of cross-sectional dependence through heterogeneous factor loadings (not shown here for the sake of brevity). The estimation consists of two stages: in the first stage the model is estimated using pooled OLS in first differences, including time dummies. Coefficients on the time dummies are then included in the main industry-by-industry estimation to account for a common dynamic effect. In the table, we report the mean-group estimates for the long-run coefficients, obtained as cross-sectional averages of industry-specific parameters, robust to the presence of outliers (Bond *et al.*, 2010). The advantage of using this estimator, compared to standard fixed effects, is that it can better account for heterogeneity across industries in the effect of the explanatory variables and control for cross-sectional dependence caused by common unknown factors, such as a global shock, technological spillovers, etc. (Eberhardt *et al.*, 2013). Tests reported in Appendix Table A.4 and A.5 point to the presence of panel unit roots and cointegration across our variables.

Results in Table 1 in columns (1) and (2) confirm the presence of capital-labour substitution, as the coefficient estimate for the total capital to value added ratio is negatively signed, and significant when we allow for heterogeneous coefficients. The impact of TFP is always negative and statistically significant, in line with earlier studies (Bassanini and Manfredi, 2012; Bentolila and Saint-Paul, 2003) These results suggest that there is large heterogeneity across industries in the effect of the capital output ratio and TFP and that failing to account for this issue may lead to biased estimates. The error correction term has the expected sign and it is always statistically significant, supporting the assumption of a long-run stationary relationship between the labour share and its determinants. The group-mean Variance Ratio (VR) panel cointegration test developed by Westerlund (2005), presented in Table 1, further confirms the presence of a cointegrating relationship.

In column (3) we extend our model to account for different types of capital assets, starting with the distinction between ICT and non-ICT capital. These results show that the capital-labour substitution is driven by ICT

Table 1: Heterogeneous capital and the labour share (long-run coefficients)

| | Homogeneous coefficients | Heterogeneous AMG coefficients | | | Heterogeneous AMG coefficients - Balanced (1981-2007) | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Total capital/value added | -0.010 | -0.070** | | | | |
| | (0.023) | (0.028) | | | | |
| Non-ICT capital/value added | | | -0.022 | -0.003 | -0.040 | -0.052 |
| | | | (0.049) | (0.062) | (0.056) | (0.064) |
| ICT capital/value added | | | -0.037*** | -0.045*** | -0.018** | -0.039*** |
| | | | (0.007) | (0.012) | (0.008) | (0.014) |
| R&D capital/value added | | | | 0.052** | | 0.025 |
| | | | | (0.021) | | (0.021) |
| TFP | -0.187*** | -0.395*** | -0.457*** | -0.372*** | -0.355*** | -0.670*** |
| | (0.032) | (0.034) | (0.053) | (0.061) | (0.063) | (0.070) |
| ECM term | -0.134*** | -0.515*** | -0.632*** | -0.750*** | -0.604*** | -0.670*** |
| | (0.005) | (0.020) | (0.023) | (0.030) | (0.025) | (0.026) |
| Obs. | 8,620 | 8,620 | 8,620 | 5,348 | 6,100 | 4,096 |
| Groups | 340 | 340 | 340 | 207 | 240 | 158 |
| VR cointegration test | -8.037*** | -10.341*** | -7.961*** | - 7.145*** | -5.814*** | -5.113*** |

**Notes:** Dependent variable is the labour share of value added. Standard errors obtained with the delta method in parentheses. Columns (1) reports results for an ECM model with homogeneous parameters. Columns (2)-(4) are Augmented Mean Group (AMG) estimates based on control for strong cross-sectional dependence (Eberhardt and Bond, 2018). ECM is the Error Correction Mechanism parameter ($\gamma_3$ in eq. 13). Columns (1)-(4) use data for an unbalanced sample of seventeen countries and twenty industries, for the 1970-2007 period. Columns (5)-(6) use data for an balanced sample sample comprising twelve countries and twenty industries for the 1981-2007 period. The group mean Variance Ratio $VR$ test has H0 of no cointegration, and H1 of cointegration in all panel units (Westerlund, 2005). *, **, *** significant at 10, 5 and 1% respectively.

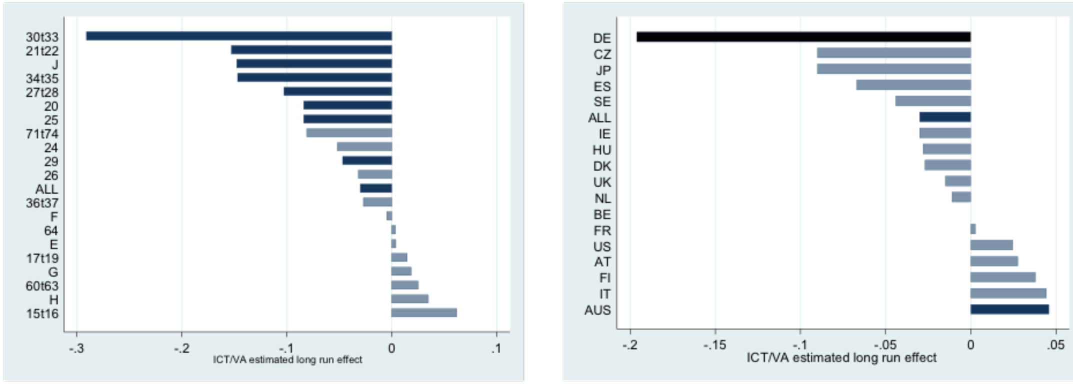
capital only, while non-ICT capital is not statistically significant. The latter implies, from a theoretical viewpoint, an elasticity of substitution between non-ICT capital and labour equal to one, i.e. the substitution effect exactly compensates the price effect, as discussed in Bassanini and Manfredi (2012). Conversely, the ICT capital-output ratio has a negative and significant effect on the labour share. ICT capital assets have spread widely over the last twenty years due to a drastic fall in relative prices, substituting many occupational tasks particularly at the intermediate skill level (Michaels *et al.*, 2014). In addition, a more recent literature has shown that the fast diffusion of ICT and the proliferation of information-intensive goods, software platforms and online services, has created the conditions for high industry concentration (Autor *et al.*, 2020), which has been linked to declining labour (and capital) shares (Barkai, 2020). This provides further support for the negative impact of ICT. In unreported robustness checks, we have also included relative prices of ICT assets but this variable turns out to be insignificant, leaving our main results unchanged. This implies that the impact of ICT is not only due to the fall in their relative prices as suggested in Karabarbounis and Neiman (2014).

In column (4) we extend our baseline specification by including a measure of knowledge capital, given by the R&D stock expressed as ratio to industry output. As discussed in Section II, this capital asset is expected to have a positive effect on the labour share, as knowledge-generating activities increase the degree of firm competitiveness. Also, innovation intensive industries are characterized by a more dynamic demand, suffer less cost-cutting pressure and have larger rents to share with workers (Aghion *et al.*, 2019b). Consistent with our expectations, the relationship between the R&D capital-output ratio and the labour share is profoundly different from tangible assets, as knowledge capital contributes to an increase of the labour share. This suggests that investments in R&D-based knowledge assets complement, rather than substitute, labour.

As discussed above, the main virtue of our dataset is of covering a relatively wide set of industries and countries for a long period of time to cover both the uptake of ICT and other intangibles assets in the economy. On the downside, our data is quite unbalanced as, for example, information for Eastern European countries such as Hungary and the Czech Republic, are only available from the early 1990s. This may raise concerns about the robustness of our estimates to sample composition. To ensure that the unbalanced nature of our sample does not affect our results, we re-estimate the specifications in columns (3) and (4) of Table 1 using a balanced sample of twelve countries covering the period between 1981 and 2007.[9] Results presented in columns (5) and (6) show that the coefficient estimates are consistent with those presented in columns (3) and (4). The R&D coefficient retains

Figure 2: Long-run coefficient estimates of ICT capital/value added, by industry and country (baseline estimates)

(A) (B)



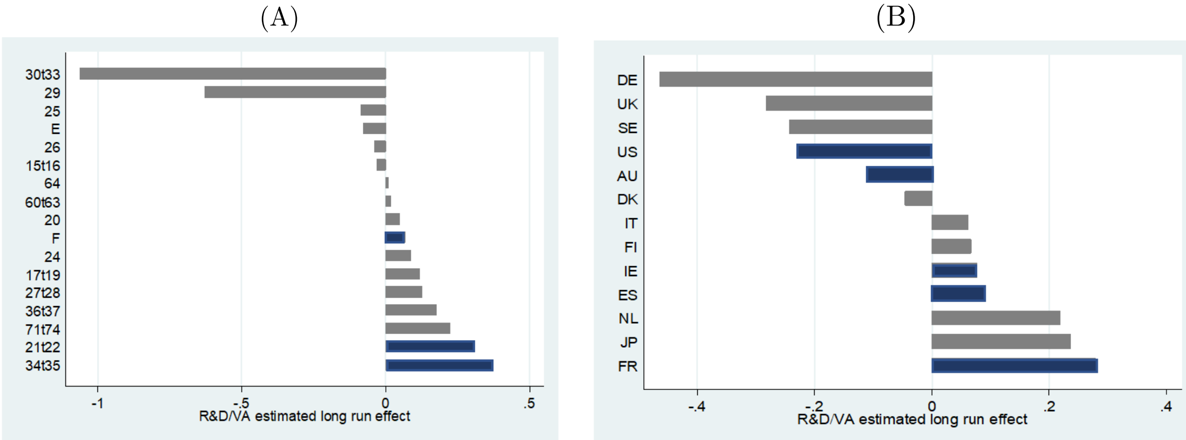

**Note:** Darker bars denote that long-run coefficients are statistically significant.

its positive sign, although it is no longer statistically significant.

We now investigate the role of ICT and R&D in driving the decline of the labour share, by re-estimating the specification in columns (3) and (4), Table 1, for each industry and country groups separately. Figure 2 presents the long-run coefficient estimates for the ICT intensity variable, for individual industries (panel A) and countries (panel B). The length of the bars identifies the size of the impact, while the darker color indicates statistical significance. Our results show that the impact of ICT is negative in the majority of industries. Positive coefficients are never statistically significant. The largest negative effect is found in electrical and optical equipment (30t33), where a 1% increase in ICT capital intensity reduces the labour share by approximately 0.3%. At the country level, the effect of the ICT capital-output ratio is only significant in two countries, Germany and Australia. Interestingly, these two countries are positioned at the two extreme points of the distribution, with Germany displaying the largest negative effect and Australia the largest positive effect. These results show that ICT capital intensity is a driver of labour share dynamics between industries, but it only marginally affects differences across countries.

Figure 3 shows the long-run coefficient estimates for R&D over value added, at the industry and country level. At the industry level, the effect tends to be mainly positive, although it is significant in only 3 industries. At the country level, the effect is positive in 7 out of 13 countries, with a significant coefficient for Finland, Ireland and France. Compared to Figure 2, the lower number of observations used to compute these estimates may contribute to the lower significance, as both the time and industry coverage of the R&D data are smaller compared to the data availability for ICT.

Figure 3: Long-run coefficient estimates of R&D, by industry and country




**Note:** Darker bars denote that long-run coefficients are statistically significant.

Overall, our long-run results give support to our first hypothesis, as we find that ICT capital contributes to the decline of the labour share. However, the assumed negative relationship between non-ICT capital and the labour share is rejected. As for our second hypothesis, our analysis so far supports the positive impact of innovative capital on the labour share. Our results are also consistent with previous work by Bentolila and Saint-Paul (2003) and Karabarbounis and Neiman (2014), who claim that industry variations in labour shares are more important than country variations. Consistent with this claim, our analysis shows that the impact of ICT is a main driver of industry trends, but not of country variations. Conversely, the impact of intangible (R&D) capital is found to be positive. Although this variable has a less robust effect than found for ICT, its positive impact appears to be quite pervasive both across sectors and countries.

# IV Labour share and heterogeneous capital: new intangible assets

In recent years, researchers have paid a great deal of attention to the changing composition of capital which, in the knowledge-based economy, is increasingly based on intangible assets. The seminal papers in this stream of literature (Corrado *et al.*, 2005 and Corrado *et al.*, 2009, CHS hereinafter) identify three main categories of intangible assets: computerised information, innovative property and economic competencies. Computerised information is not treated separately in our analysis as it largely comprises computer software, and so is part of our measure of ICT capital. Innovative property refers to the innovative activity built on a scientific base of knowledge as measured not only by conventional R&D statistics but also by innovation and new products and processes more broadly defined, including new architectural and engineering design, and new product development in the financial services industry. Therefore, this is a much wider definition compared to the knowledge capital we used in the previous section. Economic competencies include spending on strategic planning, worker training and investments to develop new markets or extend existing ones such as spending on advertising and brand development.

Since most intangible investments are not included in standard national accounts, adding these assets to the analysis of the labour share requires adjustments to both nominal and real value added. Therefore, when including intangible assets, the labour share equation is re-formulated as follows:

$$\ln S^{L*}_{ijt} = \alpha_{0ij} + \alpha_1 \ln \tilde{k}^{*}_{ijt} + \alpha_2 \ln \tilde{kint}^{*}_{ijt} + \alpha_3 \ln A^{*}_{ijt} + \epsilon_{ijt}, \tag{12}$$

where *kint* denotes intangible assets and the star superscript on the variables ($^*$) denotes that these have been constructed using adjusted value added, whilst the tilde continues to indicate that the variable is expressed as a ratio to (adjusted) value added. In the empirical analysis we further divide intangible assets into innovative property (*kinn*) and economic competencies (*kecom*) to test the hypothesis that different types of intangibles affect the labour shares in different ways. As discussed in the background section (Section I), innovative property investment is intensive in the use of skilled workers and it is likely to generate rent sharing between the firm and its employees, which would lead to a complementary relationship between this capital asset and labour. As before, we expect this to be positively related to the labour share. Economic competencies, on the other hand, are those assets most closely associated with the adoption of new technologies that require new forms of organisation, new product development and retraining of workers. As these are likely to be complementary with both ICT capital and technology more generally measured as proxied by TFP (Bresnahan *et al.*, 2002), we expect them to have a negative impact on the labour share.

## IV.1 Econometric strategy

The data used in this part of the analysis span from 1995 to 2007 (see Appendix Tables A.7 and A.8 for summary statistics). The shorter time dimension compared to the data used in Section III, prevents the implementation of dynamic panel techniques. Therefore, in this section we adopt a Fixed Effect (FE) estimator to control for cross-sectional heterogeneity; in addition, we allow our residuals to be correlated across panel units, to account for the presence of cross-sectional dependence, and within panels (Prais and Winsten, 1954). Results for the presence of cross-dependence on the variables used in this section are reported in Table A.9. We also distinguish between temporary productivity shocks and long-run impacts of technology by decomposing TFP into a trend and a cyclical component, using the Hodrick-Prescott filter. The trend component is consistent with the long-run impact of exogenous technical change, estimated in Section III. TFP is a production function residual, which captures unmeasured cyclical factor utilization and changes in production efficiency, as well as technological changes. If the labour share is anti-cyclical because of labour market rigidities and labour hoarding (Krueger, 1999, Vecchi, 2000, Hansen and Prescott, 2005) part of what has been described as a negative impact of technology could be the result of short-term cyclical productivity movements.

Results based on a FE model are likely to be affected by reverse causality. In fact, firms may decide to invest relatively more in one type of asset after achieving certain levels of labour cost shares. In this case, causality would run from the labour share to capital-output ratios. In the first part of the paper the long-run effects are estimated with the use of a dynamic specification which produces consistent estimates in the presence of simultaneity (Pesaran and Shin, 1999). In this section, we need to implement an identification strategy in an attempt to minimise endogeneity bias.

Our identification strategy rests on the assumption that the firm's decision to invest in a specific type of capital asset depends on the regulatory setting underlying the functioning of the input markets. For instance, in the early uptake of ICT in the mid-1990s, firms' investment in ICT was largely determined by the liberalisation of telecommunications services in the US (Marsh *et al.*, 2017), so regulations for this sector are used to instrument ICT capital. Similarly, as in Mason *et al.* (2019), we instrument innovative intangibles with the regulation of architectural and engineering professional services and economic competencies with the regulation of legal and accounting professional services. Therefore we use as instruments regulations which implicitly affect the cost of these types of investments. We construct two sets of indicators, one reflecting regulations within the country and the other based on regulations abroad.

Data on service regulation come from OECD Sector Regulation Indicators (Koske *et al.*, 2015). These indicators are country specific and time varying and, hence, to gauge the incidence of the regulation at the industry level, we multiply the regulation indicator with the intensity of use of the respective service in each sector. The latter is defined as the share of intermediate service purchases over total intermediates expenditure, taken at benchmark year 2000 (source: WIOD database). Full details on data sources and instruments' construction are provided in Appendix A.

Specifically, in the first stage of IV regression, we combine regulation indicators for the service inputs purchased on foreign markets, and the (general) regulation on all service inputs purchased in the home market. The latter should capture the industry attitude towards investment in capital assets in response to the general level of internal (domestic) regulation. First-stage results are reported in Appendix Table A.10. These show that coefficient estimates for our instruments are negative and statistically significant, with some variations across different type of assets. Given that larger values of our indicators signal more stringent regulations, our results are broadly consistent with the assumptions that tighter regulations decrease investments in ICT and intangible assets.

## IV.2 New intangible assets and the labour share: Results

Table 2 shows the results based on the estimation of equation (12), presenting fixed effects estimates of the impact of total intangibles (column 1) and then separating the two components, innovative properties and economic competencies (column 2). Results for the total sample show that the coefficient of non-ICT capital over value added never achieves standard levels of statistical significance, in line with estimates in Table 1. ICT capital contributes significantly to the decline of the labour share. Similarly, intangible assets show an overall negative impact on the labour share, but with an elasticity which is approximately twice as large as that of ICT capital, testifying the importance of this latest wave of innovative assets in explaining the labour share. Consistent with previous results, the impact of TFP, both trend and cycle, turns out to be negative and statistically significant.

When we distinguish between innovative properties and economic competencies (column 2) we find that the overall negative impact of intangibles is due to the economic competencies component, as expected. The result for innovative properties mirrors our earlier estimates on the impact of knowledge capital, shown in Table 1, as they positively affect the labour share.

In the last two columns we present estimates of equation (12) for a division of workers by skill level, low/medium skilled (column 3) and highly skilled (column 4) - see Appendix A for details. Results for the medium and low skilled workers are mostly in line with those for the overall sample: negative and significant impact of ICT capital, economic competencies and TFP. Overall, this suggests that new technologies are playing an important role in driving the decline of the labour share of the low skilled. However, we also find that innovative properties contribute to an increase in their labour share. This suggests that firms investing in innovations create opportunities

Table 2: The impact of intangible assets on labour share, 1995-2007 (FE-OLS estimates)

| | Total LS | | Low/intermediate skilled LS | High-skill LS |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Non-ICT capital/Value added | -0.016 | -0.019 | 0.065** | -0.029 |
| | (0.019) | (0.020) | (0.026) | (0.028) |
| ICT capital/Value added | -0.009*** | -0.011*** | -0.071*** | 0.162*** |
| | (0.003) | (0.003) | (0.004) | (0.007) |
| Intangibles/Value added | -0.033*** | | | |
| | (0.011) | | | |
| Innovative properties/Value added | | 0.055*** | 0.093*** | -0.022 |
| | | (0.016) | (0.021) | (0.025) |
| Economic competencies/Value added | | -0.038*** | -0.072*** | 0.127*** |
| | | (0.015) | (0.020) | (0.025) |
| TFP - trend | -0.217*** | -0.193*** | -0.271*** | 0.257*** |
| | (0.025) | (0.025) | (0.031) | (0.048) |
| TFP - cycle | -0.595*** | -0.555*** | -0.509*** | -0.366*** |
| | (0.027) | (0.028) | (0.036) | (0.051) |
| Groups | 300 | 300 | 300 | 300 |
| Obs. | 4120 | 4120 | 4120 | 4120 |
| R-squared | 0.902 | 0.900 | 0.982 | 0.912 |

**Notes:** Dependent variable is the labour share of value added. Robust standard errors, clustered within panels, in parentheses. Residuals are assumed to be contemporaneously correlated across panel. *, **, *** significant at 10, 5 and 1% respectively.

for improving conditions of a wider group of workers. This result is consistent with the analysis in Aghion *et al.* (2019b), where low-skilled workers employed in high-tech UK companies enjoy a higher wage premium compared not only to other low-skilled workers but also to the highly skilled. Our analysis implies that this effect is not confined to the UK but it is likely to feature in other OECD countries.

Table 3 presents the estimates using instrumental variables, as discussed above. For the total sample (column 1), results are broadly in line with those using FE, except that the ICT capital coefficient is positive, although not statistically significant. Consistent with the earlier estimates, economic competencies have a negative impact on the labour share. Similarly, coefficient estimates for low/intermediate skilled labour are broadly consistent with the results in Table 2, if we consider the direction of the effect. In fact, we find that ICT and economic competencies decrease the labour share of the low/intermediate skilled workers, while they increase the labour share of the highly skilled. Admittedly, in some cases, the size of the coefficient estimates is much inflated compared to the FE results. For example, the impact of economic competencies on the low and intermediate skilled workers jumps from -0.072 (Table 2, col. 3) to -0.532 (Table 3, col. 3). A similar reasoning applies to the coefficient of innovative activities for the highly skilled workers. These inflated coefficients could be the outcome of the instrumental variable strategy we implement. Although the performance of the tests at the bottom of Table 3 supports the validity of our instruments, the inflation of the coefficient estimates suggests that either the endogeneity issue is not fully addressed and/or there is heterogeneity in the industries' response to investments in intangible assets. In this case, our instrumental variables may pick-up the effect of one atypical group of industries (local average partial effect) rather than the average partial effect in the population (Murray, 2010).[10]

The negative effect of innovative properties assets on the labour share of the high-skilled may be explained with the fact that these investments lead to the introduction of new technologies that are substituting for 'abstract' skills, as documented in vom Lehn (2018). Another possibility is that the creative destruction process induced by large R&D investments from the mid-1990s increased the obsolescence of the skills mostly used in high value-added productive tasks. Alternatively, given that R&D expenses mainly consist of researchers' wages, the negative impact of innovative activities on the high-skill labour share might indicate that companies spending more on R&D workers seek to save on labour costs for similarly skilled groups of workers, operating outside the R&D department. Moreover, following Aghion *et al.* (2019b), the pay of the high skilled may grow more slowly than for the low skilled as a result of innovative investments, and this may lead to a fall in the labour share of the former workers as long as innovative investments affect the employment prospects of both categories similarly. However, most of these explanations are likely to be short-run temporary effects. Long-run estimates may better capture the overall (net) effect of R&D (i.e., long-run gains net of the short-term crowding out effects). In this section the time period is too short to identify the long run impacts of innovative property investments. Overall, our analysis supports the assumption that different types of capital can drive the labour share in opposite directions. Consistent with our first hypothesis *(H1)*, ICT-capital and complementary intangible assets (economic competencies) contribute to a decline of the labour share. However, we reject the assumed negative contribution of non-ICT capital. This asset type appears to complement rather than substitute labour, but is generally not significant. Our second hypothesis *(H2)* is broadly supported as innovative capital contributes to an increase in the labour share in most instances.

As a further robustness check, Appendix Table A.11 presents results based on a standard GMM regression, where we use lagged values of the endogenous variables as instruments (maximum of two lags). Here, these results confirm the overall story and the size of the effect of intangible assets are consistent with those presented in Table 2.

Table 3: The impact of intangible assets on labour share, 1995-2007 (IV-2SLS estimates)

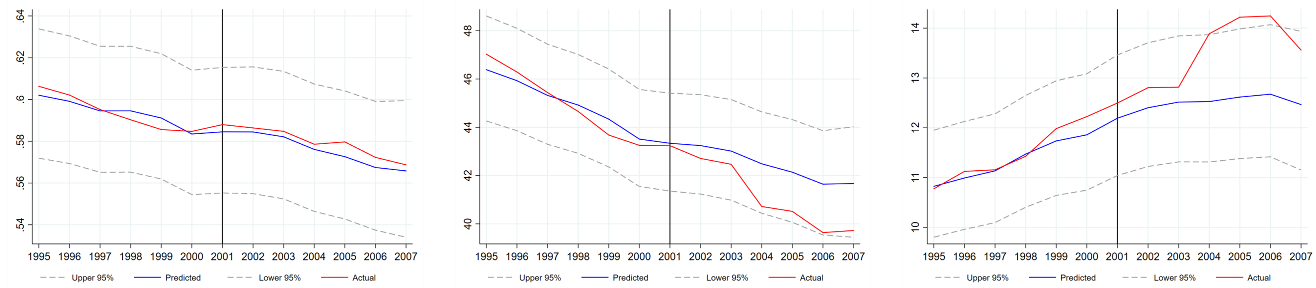
| | IV-2SLS | | |
|---|---|---|---|
| | Total LS | Low/inter-mediate skilled LS | Skilled LS |
| Non-ICT capital/Value added | 0.0280 | 0.102* | 0.120** |
| | (0.0349) | (0.053) | (0.051) |
| ICT capital/Value added | 0.0142 | -0.060*** | 0.219*** |
| | (.0112) | (0.016) | (0.023) |
| Innovative properties/Value added | 0.0450 | 0.236 | -0.589*** |
| | (0.119) | (0.154) | (0.216) |
| Economic competencies/Value added | -0.318*** | -0.532*** | 0.198 |
| | (0.0873) | (0.121) | (0.173) |
| TFP - trend | -0.363*** | -0.465*** | 0.046 |
| | (0.0980) | (0.134) | (0.183) |
| TFP - cycle | -0.684*** | -0.723*** | -0.473** |
| | (0.103) | (0.140) | (0.192) |
| Groups | 300 | 300 | 300 |
| Obs. | 3580 | 3580 | 3580 |
| Hansen J test | 0.213 | 0.156 | 0.143 |
| $p$-value | [0.644] | [0.693] | [0.706] |
| Kleibergen-Paap LM statistic | 7.164 | 6.933 | 7.164 |
| $p$-value | [0.028] | [0.031] | [0.028] |

**Notes:** Dependent variable is the labour share in value added. Robust standard errors, clustered within panel, in parentheses. Residuals are assumed to be contemporaneously correlated across panels. The instruments set is based on regulations, both foreign and domestic, of telecommunications services, architectural and engineering services and legal and accounting services. *, **, *** significant at 10, 5 and 1% respectively.

Finally, we examine the capacity of our empirical results to predict variations in the labour share over time, making use of the results from Table 2, columns (2-4). Using the year 2001 as mid-point of our time interval, we re-run the estimation for the period 1995-2001 and plot actual and predicted values for the post-2001 period in Figure 4. For the total sample and for the low-intermediate skilled group of workers, our model closely mimic the labour share dynamics as all predicted values lie within the 95% confidence interval. For the high-skilled, our model under-predicts the increasing trend in the last period of our sample. The actual data show a particularly large increase in the labour share of the highly skilled between 2003 and 2006, which is not picked up by our predictions.

Figure 4: Labour share out-of-sample prediction: 1995-2001 and 2001-2007

Total sample | Low- and intermediated skilled | High-skilled




**Note:** Predictions for the post-2001 period. These values are based on estimates presented in Table 2 and use data between 1995 and 2001.

# V Conclusions

This paper provides a novel contribution to the debate on the determinants of the decline of the labour share, by focusing on the different types of capital assets used by firms. Previous analyses did not fully explore the possibility that capital and labour can be substitutes or complements depending on the nature of capital. Overall, we find that both ICT capital assets and economic competencies decrease the labour share (substitution effect), while innovative capital, measured using a variety of proxies, is characterised by a complementary relationship. Results are consistent across two datasets which vary by time period and types of assets and different model specifications and estimation methods. In most specifications, we also find that technological progress, proxied by TFP, contributes to the decline in the labour share, a result that we share with earlier contributions. The analysis in this paper also highlights the fact that the substitution/complementary effects not only depend on the type of capital but also depend on the type of labour. We find that the highly educated are particularly sheltered from the negative impact of technology, and they are mainly complements, rather than substitutes, for the different types of capital assets, with the possible exception of innovative capital. Results for the low and intermediate skilled, on the other hand, are negatively impacted by ICT capital, intangible economic competencies and technology (TFP). In contrast, intangible capital capturing innovative activities appears to promote the increase in the labour share of this group of workers, suggesting a complementary relationship. Our results are important as they shed light on the discussion on the size of the elasticity of substitution between capital and labour. Focusing on the elasticity of substitution between a single labour and a single capital input is a very limited way of looking at modern production, characterised by increasing capital and labour heterogeneity.

The results in this paper are consistent with the superstar firm literature which emphasises that markets have become less competitive due to the nature of the recent digital technology revolution. Digital technological developments, however, have led to increased investment in intangible capital as complementary inputs, and these are likely to be spread across a broader spectrum of firms. In addition, increased markups, on their own may not be sufficient to drive a decline in the labour share, if these firms shared more of their rents with workers as discussed in Bell et al. (2018). These authors' findings that the fall in rent sharing was more pronounced among high markup firms, points to an important role for the decline in the bargaining power of workers.

As intangible assets are poorly measured in official datasets, it is difficult to disentangle whether increases in reported profits are due to firms' returns on their intangible investments or above normal profits due to market concentration, and how they are impacted by institutions such as union power. Disentangling these influences is an important area for future research. In this context, measuring the different types of capital becomes crucial. Recent debate on the nature of intangibles has identified some problematic issues in aggregate or industry level measures of intangible capital. For example, in the case of intellectual properties, globalisation leads to a divergence between ownership and use across national borders which are not accounted for in current intangibles datasets. Firm level measures of intangible investments are difficult to construct, especially given accounting conventions where expenditures relating to economic competencies, as well as some intellectual property, are not identified as assets. There is an urgent need for statistical offices, in collaboration with the academic community, to develop better measures of intangible assets, both at the aggregate and firm level.

# Online Appendix

## Data sources and methods: Industry accounts data

We draw data from a number of different sources. Our main source for calculating the labour share is the EU KLEMS database which contains harmonised data on outputs, inputs and productivity on an industry basis annually for a sample of EU countries and a number of other high income economies such as Australia, Japan and the US. The labour share is constructed as the ratio of payments to labour (variable $LAB$ in EUKLEMS) to nominal value added ($VA$). Following national accounting conventions, $LAB$ includes not just wages and salaries but also other non-wage labour costs paid by employers such as pension contributions. It also includes an imputation for the labour payments to the self employed, since their remuneration is included as mixed income in national accounts, assuming that their compensation equals the industry average for employees.This issue has recently been shown to be important for understanding the dynamics of the labor share (Gutierrez and Piton, 2020). An alternative would have been to restrict the analysis to employees only. Our regression results, however, were found to be robust to using employee labour shares. Therefore, we prefer to use the broader measure as not doing so misses a large component of labour input which has been growing in importance over time.

Tangible capital inputs were also taken from EU KLEMS and are measured as capital services, consistent with the standard approach employed in growth accounting e.g. as used in Jorgenson and Stiroh (2000). To analyse the separate impact of ICT and non-ICT capital, EU KLEMS divides capital input growth into two groups of assets: ICT and non-ICT which themselves are aggregates of more detailed capital assets. ICT includes computer hardware, software and communications equipment. Non-ICT assets largely consists of other plant and machinery, transport equipment, structures and some intangible assets such as mineral oil exploration and artistic originals that were part of the national accounts when this version of EU KLEMS was developed. Residential buildings are excluded as is the real estate sector from the output side. Aggregation across these asset types is based on weighting individual assets by their share of the value of capital, which in turn are based on user costs of capital. The 2009 release of EU KLEMS includes a division of the workforce into low, medium and high skilled. The latter group includes workers with a university degree or equivalent, and this skill level is broadly comparable across countries. Medium skills generally comprise vocational qualifications and any certified skills above high school but below degree level. Here there is less comparability across countries, with some classifying low level vocational certifications as medium skilled while others considering them as part of the low skill group. Therefore we aggregated low and medium skills into one group. Total factor productivity ($TFP$) growth is measured as the residual between output growth and the share weighted growth in inputs, with weights equal to each inputs' share of the value of output, averaged across adjacent time periods. Details of the growth accounting methodology, and data sources are available in O'Mahony and Timmer (2009).

In section III, R&D expenses were extracted from the OECD ANBERD 2002 and 2006 dataset. R&D capital is built by means of the perpetual inventory method, cumulating real R&D expenses and assuming an annual geometric depreciation rate of 15%. The value of capital stock at the initial year is computed with the formula devised by Hall and Mairesse (1995). As stated in the main text, the construction of intangible assets follows the method of CHS, (Corrado *et al.*, 2005 and Corrado *et al.*, 2009), which divides intangibles into Innovative Property and Economic Competencies. Innovative Property refers to innovative activity including conventional R&D capital but also innovation and new products and processes more broadly defined, including new architectural and engineering design, and new product development costs in the financial industry. Economic competencies include spending on strategic planning, worker training and investments to develop new markets or extend existing ones such as spending on advertising and brand development. Note in our main database, EU KLEMS, software, mineral exploration and artistic originals are already included in its capital aggregates and so they are not part of intangible capital ($kint$). Most of the assets include in $kint$ lie outside the current System of National Accounts (SNA) boundaries for capital assets. Software, mineral exploration and the artistic originals part of design have been in the national accounts for some time following the SNA1993 guidelines and scientific R&D expenditures have been added, following the SNA2008 revisions. The categories included in national accounts currently represent less than one third of all intangibles according to the CHS definition in the US and in European countries. The estimates of intangible assets at the industry level for EU countries are taken from Niebel *et al.* (2016). These take the aggregate market economy estimates from the INTAN Invest platform, described in Corrado *et al.* (2017), and use data from supply use tables and labour force surveys (the occupation classifications of the workforce and on the job training propensities) to divide these aggregates by industry. To these were added data for the US developed by the Conference Board and for Japan developed by Fukao *et al.* (2009). Since most intangible investments are not included in standard national accounts adding these assets to the analysis of the labour share requires adjustments to both nominal and real value added. Intangible assets involve both purchased assets (such as new architectural and engineering designs, market research and advertising expenditures) and own account (own account development of organizational structures, investments in firms' specific human capital) measures. Purchased intangibles were previously classified to intermediate expenditures and so value added needs to rise to reflect the reclassification to investment goods. Own account development of intangible assets within firms means that a component of output was previously missing and therefore value added is also affected. The calculations required to undertake the adjustments, as well as those to capitalise intangibles and adjust the rates of return on capital are given in Niebel *et al.* (2016). In addition to constructing nominal investment series, the research had to decide on appropriate deflators to convert to volume measures and on the form and rates of depreciation to capitalise these assets. GDP deflators were generally employed due to lack of information on asset-specific deflators. Studies varied on the precise depreciation rates but in all estimates, the rates were much higher than is generally assumed for tangible capital.

Finally, all monetary variables are made comparable using the relative PPP of industry output (1997 base), following Inklaar and Timmer (2008). In the estimation, all capital variables are expressed as ratios to industry real value added, again taken from EU KLEMS.

## Instrumental variables' construction

We predict firm investment in various capital assets using cross-country cross-industry variation in the regulatory setting underlying the functioning of the input markets. As in Marsh *et al.*, 2017, we instrument ICT capital using time-varying indicators reflecting the extent of telecom service regulation ($REG^T$). To predict variation in intangible investments, we look at regulation, which implicitly affects the cost of these investments, compared to the purchases of the corresponding service on the market. Similarly to Mason *et al.* (2019) we instrument innovative property intangibles with the regulation of architectural and engineering professional services ($REG^E$), which is a close substitute for internal R&D. For economic competencies, we consider the regulation of legal and accounting professional services ($REG^A$).

Data on service regulation come from OECD Sector Regulation Indicators (see Koske *et al.*, 2015). Regulation indicators are country specific and available at 5-year intervals since 1998; accordingly, these values are kept constant in intermediate years. In order to gauge the incidence of the regulation at the industry level, we multiply the regulation indicator of the selling service sector with the intensity of use of the respective service in each purchasing sector. The usage intensity of each purchasing industry is defined as the share of intermediate service purchases over total intermediates expenditure, taken at the benchmark year 2000 (below denoted by $b$). Inter-industry intermediates transactions come from the WIOD database (World Input-Output Database, available at www.wiod.org).

Formally, each instrumental variable ($Z^S$) is built as:

$$Z^S_{ijt} = \sum_i \sum_j \omega^S_{ijb} \times REG^S_{jt} \qquad with \qquad \omega^S_{ijb} = \frac{REG\_PUR^S_{ijb}}{TOT\_PUR_{ib}}$$

where the superscript $S$ indicates the type of regulated services purchased with $S = T, E, A$ (i.e. telecom, architect and engineering professional services, legal and accounting professional services, respectively). $REG\_PUR^S_{ijb}$ are purchases of the regulated service $S$ of industry $i$ from country $j$, whilst $TOT\_PUR_{ib}$ are total intermediate input purchases of industry $i$ at the benchmark year $b$. Both $REG\_PUR^S_{ijb}$ and $TOT\_PUR_{ib}$ are expressed at current prices.

In the first stage of the 2SLS-IV regression, the set of instruments includes individual indicators of foreign regulation ($T$, $A$, and $E$ separately), as well as the average level of regulation of these services in the home market (the weighting scheme is based on the formula shown above). The latter variable should capture the industry attitude towards investment in capital assets in response to the general level of internal (domestic) regulation.

Unreported estimates show that our results are robust to using alternative weighting schemes: (i) time-varying input-output weights; (ii) weights based on intermediate sales rather than purchases; and (iii) intermediate input-output weights from a benchmark country such as the US. These results are available from the authors upon request.

## Data analysis

Table A.1 Aggregate labour share and sectoral capital-to-output ratio: comparative statics

| | | *A- Within Effect* | |
|---|---|---|---|
| | $\sigma_I$ | subject to: | $\partial S_I^L / \partial \tilde{k}_I$ |
| A.1 | $> 0$ | always | $> 0$ |
| A.2 | $< 0$ | always | $< 0$ |
| | | *B- Between Effect* | |
| | $\epsilon$ | subject to: | $\partial \theta_I / \partial \tilde{k}_I$ |
| B.1 | $< 0$ | always | $> 0$ |
| B.2 | $> 0$ | $Y_I/Y < \phi_I^{1/\epsilon}$ | $> 0$ |
| B.3 | $> 0$ | $Y_I/Y > \phi_I^{1/\epsilon}$ | $< 0$ |

Table A.2. Average values at country level: Long Run (1970-2007)

| | | labour Share | Non-ICT Capital/Value added | ICT Capital/Value added | R&D Capital/Value added | TFP |
|---|---|---|---|---|---|---|
| Austria | AT | 0.70 | 0.70 | 0.04 | 0.17 | 0.81 |
| Australia | AU | 0.72 | 0.55 | 0.04 | 0.10 | 0.77 |
| Belgium | BE | 0.67 | 0.57 | 0.03 | 0.19 | 1.29 |
| Czech Rep. | CZ | 0.58 | 0.57 | 0.07 | 0.08 | 0.71 |
| Germany | DE | 0.75 | 0.40 | 0.03 | 0.18 | 0.99 |
| Denmark | DK | 0.73 | 0.52 | 0.04 | 0.14 | 1.06 |
| Spain | ES | 0.65 | 0.40 | 0.03 | 0.05 | 0.95 |
| Finland | FI | 0.71 | 0.51 | 0.03 | 0.12 | 1.02 |
| France | FR | 0.71 | 0.39 | 0.04 | 0.20 | 1.05 |
| Hungary | HU | 0.67 | 0.47 | 0.06 | 0.08 | 0.72 |
| Ireland | IE | 0.64 | 0.64 | 0.03 | 0.05 | 1.18 |
| Italy | IT | 0.72 | 0.53 | 0.03 | 0.07 | 1.00 |
| Japan | JP | 0.64 | 0.72 | 0.05 | 0.28 | 0.65 |
| Netherlands | NL | 0.72 | 0.59 | 0.04 | 0.20 | 1.00 |
| Sweden | SE | 0.81 | 0.50 | 0.09 | 0.25 | 1.08 |
| United Kingdom | UK | 0.73 | 0.39 | 0.03 | 0.14 | 1.07 |
| United States | US | 0.68 | 0.35 | 0.04 | 0.26 | 1.00 |
| TOTAL | | 0.70 | 0.51 | 0.04 | 0.15 | 0.97 |

Table A.3. Average values at industry level: Long Run (1970-2007)

| | | labour Share | Non-ICT Capital/Value added | ICT Capital/Value added | R&D Capital/Value added | TFP |
|---|---|---|---|---|---|---|
| Food | 15t16 | 0.62 | 0.55 | 0.02 | 0.06 | 0.90 |
| Textiles | 17t19 | 0.81 | 0.61 | 0.02 | 0.05 | 0.58 |
| Wood | 20 | 0.76 | 0.49 | 0.02 | 0.02 | 0.91 |
| Paper | 21t22 | 0.68 | 0.48 | 0.05 | 0.03 | 0.82 |
| Chemicals | 24 | 0.53 | 0.63 | 0.02 | 0.53 | 1.46 |
| Rubber | 25 | 0.71 | 0.36 | 0.01 | 0.11 | 2.08 |
| Non-met. min. | 26 | 0.68 | 0.48 | 0.02 | 0.08 | 1.42 |
| Basic metals | 27t28 | 0.70 | 0.50 | 0.02 | 0.07 | 0.90 |
| Machinery, nec | 29 | 0.75 | 0.26 | 0.02 | 0.21 | 0.92 |
| Electrical Eq. | 30t33 | 0.73 | 0.46 | 0.06 | 0.68 | 0.88 |
| Transport Eq. | 34t35 | 0.77 | 0.77 | 0.06 | 0.41 | 0.40 |
| Manufacturing, nec | 36t37 | 0.88 | 0.25 | 0.02 | 0.05 | 1.28 |
| Transport | 60t63 | 0.73 | 0.54 | 0.05 | 0.01 | 0.73 |
| Post & Telecom | 64 | 0.55 | 0.40 | 0.11 | 0.05 | 1.11 |
| Business Services | 71t74 | 0.76 | 0.40 | 0.10 | 0.08 | 0.62 |
| Utilities | E | 0.37 | 1.86 | 0.05 | 0.04 | 0.53 |
| Construction | F | 0.82 | 0.14 | 0.01 | 0.01 | 0.96 |
| Wholesale, retail | G | 0.75 | 0.26 | 0.03 | 0.02 | 1.10 |
| Hotels | H | 0.86 | 0.53 | 0.03 | . | 0.65 |
| Fin. Intermediation | J | 0.59 | 0.29 | 0.06 | 0.02 | 1.16 |
| TOTAL | | 0.70 | 0.51 | 0.04 | 0.15 | 0.97 |

Table A.4. Panel unit roots test (Pesaran, 2007)

| | labour share | Total capital/ Value added | Non-ICT capital/ Value added | ICT capital/ Value added | R&D capital/ Value added | TFP |
|---|---|---|---|---|---|---|
| Z[t-bar] | 5.05 | 7.68 | 20.06 | 8.22 | 28.25 | 10.50 |
| $p$-value | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |

**Notes:** H0: all panel units contain unit roots, I(1). All variables expressed in logs. Number of lags=3.

Table A.5. Test for cross-sectional dependence: Long Run (1970-2007)

| | CD-test | p-value | corr | abs(corr) |
|---|---|---|---|---|
| Labour share | 152.32 | 0.000 | 0.111 | 0.389 |
| Non-ICT capital/Value added | 20.17 | 0.000 | 0.015 | 0.535 |
| ICT capital/Value added | 1019.49 | 0.000 | 0.815 | 0.856 |
| R&D capital/Value added | 201.5 | 0.000 | 0.188 | 0.666 |
| TFP | 174.48 | 0.000 | 0.154 | 0.567 |

**Notes:** The null hypothesis is of cross-sectional independence across panel units. All variables are expressed in logs.

Table A.6. Heterogeneous capital and the labour share, ARDL(2,2) (long-run coefficients)

| | Homogeneous coefficients | Heterogeneous AMG coefficients | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Total capital/Value added | -0.001 | -0.092*** | | |
| | (0.024 | (0.004) | | |
| Non-ICT capital/Value added | | | -0.047 | -0.038*** |
| | | | (0.060) | (0.015) |
| ICT capital/Value added | | | -0.025*** | -0.026*** |
| | | | (0.005) | (0.015 |
| R&D capital /Value added | | | | 0.023* |
| | | | | (0.014) |
| Total Factor Productivity (TFP) | -0.175*** | -0.397*** | -0.409*** | -0.327*** |
| | (0.034) | (0.038) | (0.065) | (0.000) |
| ECM term | -0.137*** | -0.502*** | -0.586*** | -0.693*** |
| | (0.006) | (0.020) | (0.022) | (0.030) |
| Obs. | 8,280 | 8,280 | 7,840 | 4,648 |
| Groups | 340 | 340 | 300 | 172 |

**Notes:** Dependent variable is the labour share in value added. Standard errors obtained with the delta method in parentheses. Columns (1) reports results for an ECM model with homogeneous parameters. Columns (2)-(4) are Augmented Mean Group (AMG) estimates based on control for strong cross-sectional dependence (Eberhardt and Bond, 2018). the ECM term is the Error Correction Mechanism parameter ($\gamma_3$ in eq. 13). *, **, *** significant at 10, 5 and 1% respectively.

Table A.7. Average values at country level: Short Run (1995-2007)

| | AT | BE | CZ | DE | DK | ES | FI | FR |
|---|---|---|---|---|---|---|---|---|
| labour share | 0.58 | 0.61 | 0.58 | 0.68 | 0.65 | 0.60 | 0.60 | 0.64 |
| TFP | 1.17 | 1.05 | 1.13 | 1.09 | 0.99 | 0.97 | 1.16 | 1.15 |
| Non-ICT capital/ VA | 0.03 | 0.03 | <0.01 | <0.01 | 0.01 | 0.01 | 0.06 | 0.01 |
| ICT capital/VA | 0.10 | 0.08 | 0.01 | 0.01 | 0.03 | 0.02 | 0.11 | 0.01 |
| Intangibles capital/VA | 0.27 | 0.30 | 0.20 | 0.32 | 0.27 | 0.17 | 0.31 | 0.31 |
| Innovative properties/VA | 0.18 | 0.19 | 0.13 | 0.23 | 0.18 | 0.09 | 0.20 | 0.20 |
| Economic comp./VA | 0.07 | 0.09 | 0.06 | 0.08 | 0.09 | 0.05 | 0.09 | 0.08 |

| | HU | IE | IT | JP | NL | SE | UK | US |
|---|---|---|---|---|---|---|---|---|
| labour share | 0.59 | 0.58 | 0.64 | 0.57 | 0.62 | 0.62 | 0.67 | 0.59 |
| TFP | 1.33 | 1.11 | 1.01 | 1.01 | 1.09 | 1.14 | 1.06 | 1.08 |
| Non-ICT capital/ VA | <0.01 | 0.15 | 0.01 | <0.01 | 0.03 | <0.01 | 0.01 | 0.001 |
| ICT capital/VA | <0.01 | 0.41 | 0.01 | <0.01 | 0.07 | 0.01 | 0.02 | <0.01 |
| Intangibles capital/VA | 0.20 | 0.15 | 0.19 | 0.31 | 0.28 | 0.37 | 0.28 | 0.34 |
| Innovative properties/VA | 0.09 | 0.08 | 0.13 | 0.27 | 0.16 | 0.25 | 0.13 | 0.21 |
| Economic comp./VA | 0.09 | 0.06 | 0.05 | 0.05 | 0.10 | 0.09 | 0.14 | 0.10 |

**Notes:** Austria (AT), Australia (AU), Belgium (BE), Czech Rep. (CZ), Germany (DE), Denmark (DK), Spain (ES), Finland (FI), France (FR), Hungary (HU), Ireland (IE), Italy (IT), Japan (JP), Netherlands (NL), Sweden (SE), United Kingdom (UK), United States (US),

Table A.8. Average values at indstry level: Short Run (1995-2007)

| | 15t16 | 17t19 | 20 | 21t22 | 24 | 25 | 26 | 27t28 | 29 | 30t33 |
|---|---|---|---|---|---|---|---|---|---|---|
| labour share | 0.56 | 0.74 | 0.69 | 0.59 | 0.38 | 0.60 | 0.59 | 0.66 | 0.66 | 0.576 |
| TFP | 1.00 | 1.08 | 1.12 | 1.09 | 1.07 | 1.16 | 1.08 | 1.05 | 1.10 | 1.45 |
| Non-ICT capital/ VA | 0.01 | 0.04 | 0.07 | 0.01 | 0.01 | 0.04 | 0.03 | 0.02 | 0.03 | 0.01 |
| ICT capital/VA | 0.02 | 0.09 | 0.20 | 0.04 | 0.02 | 0.08 | 0.09 | 0.03 | 0.04 | 0.02 |
| Intangibles capital/VA | 0.23 | 0.20 | 0.14 | 0.18 | 0.87 | 0.38 | 0.26 | 0.20 | 0.35 | 0.52 |
| Innovative properties/VA | 0.13 | 0.09 | 0.06 | 0.08 | 0.75 | 0.29 | 0.18 | 0.12 | 0.25 | 0.41 |
| Economic comp./VA | 0.09 | 0.10 | 0.07 | 0.09 | 0.08 | 0.07 | 0.07 | 0.07 | 0.08 | 0.07 |
| | 34t35 | 36t37 | 60t63 | 64 | 71t74 | E | F | G | H | J |
| labour share | 0.63 | 0.75 | 0.66 | 0.45 | 0.67 | 0.31 | 0.77 | 0.67 | 0.77 | 0.52 |
| TFP | 1.20 | 1.07 | 1.02 | 1.30 | 0.96 | 1.08 | 0.97 | 1.10 | 0.95 | 1.09 |
| Non-ICT capital/VA | 0.04 | 0.06 | 0.01 | 0.01 | 0.01 | 0.02 | 0.01 | <0.01 | 0.02 | <0.01 |
| ICT capital/VA | 0.15 | 0.15 | 0.02 | 0.02 | 0.01 | 0.07 | 0.02 | 0.01 | 0.04 | 0.01 |
| Intangibles capital/VA | 0.39 | 0.26 | 0.10 | 0.14 | 0.32 | 0.11 | 0.13 | 0.16 | 0.13 | 0.25 |
| Innovative properties/VA | 0.30 | 0.16 | 0.03 | 0.08 | 0.15 | 0.05 | 0.05 | 0.05 | 0.04 | 0.11 |
| Economic comp. /VA | 0.07 | 0.10 | 0.07 | 0.05 | 0.12 | 0.06 | 0.07 | 0.09 | 0.08 | 0.12 |

**Notes:** Food (15t16), Textiles (17t19), Wood (20), Paper (21t22), Chemicals (24), Rubber (25), Non-met. min. (26), Basic metals (27t28), Machinery, nec (29), Electrical Eq. (30t33), Transport Eq. (34t35), Manufacturing, nec (36t37), Transport (60t63), Post, Telecom (64), Business services (71t74), Utilities (E), Construction (F), Wholesale, retail (G), Hotels (H), Fin. Intermediation (J).

Table A.9. Test for cross-sectional dependence: Short Run (1995-2007)

| | CD-test | p-value | corr | abs(corr) |
|---|---|---|---|---|
| Labour share | 44.75 | 0.000 | 0.055 | 0.399 |
| Non-ICT capital/Value added | 30.83 | 0.000 | 0.038 | 0.555 |
| ICT capital/Value added | 576.77 | 0.000 | 0.715 | 0.818 |
| Intangibles capital/Value added | 122.64 | 0.000 | 0.152 | 0.573 |
| Innovation property capital/Value added | 73.34 | 0.000 | 0.090 | 0.551 |
| Economic comp. capital/Value added | 9.69 | 0.000 | 0.012 | 0.535 |
| TFP - trend | 105.95 | 0.000 | 0.130 | 0.991 |
| TFP - cycle | 31.90 | 0.000 | 0.040 | 0.369 |

**Notes:** The null hypothesis is of cross-sectional independence across panel units. All variables are expressed in logs.

Table A.10. Instrumental variable estimation. First stage

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| | Total Labour Share | | | Low & Interm. Skilled Labour Share | | | High Skilled Labour Share | | |
| | ICT/VA | Innov. Prop./ VA | Eco- nomic comp./ VA | ICT/VA | Innov. Prop./ VA | Eco- nomic comp./ VA | ICT/VA | Innov. Prop./ VA | Eco- nomic comp./ VA |
| Foreign telecom services regulation, LN (t-1) | -0.447*** | -0.002 | -0.096*** | -0.364*** | -0.006 | -0.101*** | -0.447*** | -0.002 | -0.096*** |
| | (0.056) | (0.016) | (0.019) | (0.064) | (0.018) | (0.022) | (0.056) | (0.016) | (0.019) |
| Foreign legal and accounting services regulation, LN (t-1) | -0.382 | 0.097 | 0.352*** | -0.720*** | 0.071 | 0.186*** | -0.382 | 0.097 | 0.352*** |
| | (0.296) | (0.085) | (0.110) | (0.236) | (0.067) | (0.092) | (0.296) | (0.085) | (0.110) |
| Foreign architect and engineering services regulation, LN (t-1) | 0.065 | -0.100*** | 0.021 | 0.064** | -0.105*** | -0.003 | 0.065 | -0.100*** | 0.021 |
| | (0.055) | (0.025) | (0.093) | (0.052) | (0.022) | (0.022) | (0.065) | (0.025) | (0.022) |
| Total professional services regulation (weighted mean), LN (t-1) | -0.990*** | -0.042 | -0.323*** | -1.137*** | 0.019 | -0.052 | -0.990*** | -0.042 | -0.322** |
| | (0.291) | (0.091) | (0.112) | (0.269) | (0.074) | (0.105) | (0.291) | (0.091) | (0.111) |
| *R*-squared | | | | | | | | | |
| Obs. | 3,580 | 3,580 | 3,580 | 3,580 | 3,580 | 3,580 | 3,580 | 3,580 | 3,580 |
| Tests of excluded IV F(6, 3271), P value | <0.001 | 0.011 | <0.001 | <0.001 | 0.008 | 0.002 | <0.001 | 0.011 | <0.001 |
| Sanderson-Winmejer F(4, 3271), P value | 0.024 | 0.003 | 0.024 | 0.019 | 0.003 | 0.023 | 0.024 | 0.003 | 0.024 |

**Notes:** *, **, *** significant at 10, 5 and 1% respectively. Robust standard errors are displayed in brackets.

Table A.11. GMM estimation (Hansen 1982)

| | (1) Total LS | (2) High-skilled LS | (3) Low/inter-mediate skilled LS |
|---|---|---|---|
| TFP - trend | -0.176*** | 0.562*** | -0.324*** |
| | (0.049) | (0.095) | (0.060) |
| TFP - cycle | -0.480*** | -0.039 | -0.550*** |
| | (0.043) | (0.087) | (0.053) |
| Non-ICT capital/Value added | 0.013 | 0.170*** | 0.060 |
| | (0.028) | (0.056) | (0.042) |
| ICT capital/Value added | 0.004 | 0.162*** | -0.069** |
| | (0.025) | (0.048) | (0.029) |
| Innovative properties/Value added | 0.037 | 0.017 | 0.025 |
| | (0.030) | (0.056) | (0.038) |
| Economic competencies/Value added | -0.062** | 0.129** | -0.085** |
| | (0.032) | (0.065) | (0.039) |
| Groups | 320 | 320 | 320 |
| Obs. | 3,480 | 3,480 | 3,480 |
| $R$-squared | 0.1813 | 0.2645 | 0.2569 |
| Hansen J test | 0.048 | 0.335 | 0.028 |
| (p-value) | [0.827] | [0.563] | [0.867] |
| Kleibergen-Paap LM statistic | 74.393 | 74.393 | 74.393 |
| (p-value) | [<0.001] | [<0.001] | [<0.001] |

**Notes:** Robust standard errors are displayed in brackets. ICT capital, innovative properties and economic competencies have been instrumented with their lagged values at time (t-1) and (t-2). *, **, *** significant at 10, 5 and 1% respectively.

# Notes

[1]A decline in rent sharing results from weaker bargaining position of workers as the result of technology change (robotization), higher labour mobility and institutional changes (decline in unions and competition policies). Companies with higher market power experience relatively larger falls in rent sharing, consistent with the evidence on concentration and the decline of the labour share discussed above.

[2]Innovations can take the form of product and process innovations and the two can have different effects on rent sharing. According to Van Reenen (1996), the effect of the former on wages should be larger as they are likely to be more firm-specific. Indeed, innovators are expected to enjoy some market power to pay for their innovations (Arrow, 1972, Levin *et al.*, 1987). On the other hand, Hildreth (1998) shows that rent-sharing mainly occurs as the result of process innovation, following cost-reduction.

[3]This formulation exploits the assumption of constant returns to scale at the economy wide level ($\theta_I = 1 - \theta_N$).

[4]https://ec.europa.eu/eurostat/cache/metadata/Annexes/htec_esms_an3.pdf

[5]This occurs as the expansion of $Y_I$ crowds out $Y_N$ (i.e. when $\epsilon < 0$) or as, when both productions expand, the increase in $Y_I$ dominates that in $Y_N$ since the relative price of the former good increases ($\epsilon > 0$ with low values). This manifests when the real output ratio $Y_I/Y$ is relatively low, i.e. below the threshold $\phi_I^{1/\epsilon}$.

[6]This occurs when $Y_I/Y$ is relatively high, i.e. above the threshold $\phi_I^{1/\epsilon}$. Note that, as a relevant special case, when $\epsilon = 0$, aggregate output is combined as a Cobb-Douglas technology and the between-effect vanishes.

[7]Following Bassanini and Manfredi (2012), we exclude Agriculture, Mining, Refining and Petroleum and Real estate activities as well as the non-market service sectors Public Administration, Education and Health.

The exclusions are motivated by weak output measures (real estate output is mostly imputed rents and in some countries public services are measured by inputs), high degree of regulation (Agriculture) and volatility of output (Mining, Petroleum Refining).

[8]Results for a richer dynamic specification, ARDL(2,2), are presented in Appendix Table A.6.

[9]The balanced sample includes: Australia, Belgium, Denmark, Finland, France, Hungary, Italy, Japan, Netherlands, Spain, UK, US.

[10]A similar pattern in estimated coefficients from FE to IV regression is found by Aghion *et al.* (2019a) in a study on the impact of innovation on income inequality.

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