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

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# Introduction

There is considerable evidence that labor'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 labor share decline include market regulations (Azmat *et al.*, 2012), globalization (Elsby *et al.*, 2013), measurement issues (Koh *et al.*, 2018), technological change (Bassanini and Manfredi, 2012), and market concentration (Autor *et al.*, 2017a). 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 labor input. This implies that the capital share can include excess rents (Autor *et al.*, 2017b, Barkai, 2016), the mis-allocation of the labor 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 labor share has considered a single capital asset, which can either substitute or complement labor. One of the main arguments is that advances in 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 productions (Karabarbounis and Neiman, 2014). In contrast, Lawrence (2015) claims that rapid labor augmenting technical change has led to a decline of the effective capital labor ratio, and given the complementarity between capital and labor, has decreased the labor share. Both approaches ignore the possibility that capital and labor 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 labor share.

To guide our empirical analysis, we first develop a theoretical (multi-sector) framework where variation in the aggregate labor share is 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. Our set-up distinguishes between different types of workers as technology and capital heterogeneity are likely to affect the labor share in different ways, depending on the skill level.

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 the traditional measure of intangible capital, R&D capital stock. Our estimation procedure fully exploits the longitudinal and time-series variation of the data, by estimating an Error Correction Model (ECM) and controlling for 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, when the lag structure of the variables is correctly specified (Pesaran and Shin, 1999). In addition, the inclusion of controls for cross-sectional dependence can reasonably account for omitted variable bias.

Second, we focus on the determinants of the labor 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. As shown in numerous earlier studies, the latter type of intangible investments are necessary to benefit from the adoption of new technologies (see Bertschek and Kaiser, 2004; Black and Lynch, 2001; Bresnahan *et al.*, 2002). 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. Examples include the regulation of telecommunications services and of architectural and engineering professional services as developed in Koske *et al.* (2015).

Our results show that, while exogenous technical change always contributes to the decline of the labor share, the different types of capital assets drive the labor share in different directions. In the long run estimates, ICT capital plays a major role in driving the decline in the labor 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. The impact of ICT differs over different types of workers, with a negative effect only on the wage bill share of the low and intermediate skilled. This is consistent with earlier results on skill biased technical change (Autor *et al.*, 1998). In contrast, R&D appears to raise the labor share as these activities create rents that are likely shared by all workers (Aghion *et al.*, 2017). Overall, our dynamic specification predicts a 14.9% fall in the labor share, since the the 1970s, compared to an 11.1% observed in the data. Using new estimates of intangible capital, in the second part of our analysis, we find that economic competencies, together with ICT, have the strongest negative impact, accounting for 21% and 19% (respectively) of the decline in the labor share. Economic competencies are the components of intangibles that mostly complement investment in ICT. The negative effect is again confined to low and intermediate skilled workers. Conversely, the labor shares of the highly skilled are particularly immune to exogenous technical change, ICT and economic competencies. Finally, the second main component of intangible assets, innovative properties, has a mostly positive impact on the labor share, consistent with the results from the long-run dynamic specification. Overall, our study concludes that the type of capital assets matters and accounting for capital heterogeneity is crucial to understand movements in the labor share.

The present paper contributes to several important streams of the literature. We contribute to the debate on the drivers of the labor share dynamics stressing how this pattern is affected by the firms' increasing investments in new capital types. Specifically, our work extends the analysis by Koh *et al.* (2018) to a cross-country, cross-industry setting, showing that intangibles explain an important part of changes in the labor share. However, their effect 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 labor). Our work also extends the analysis of intangible capital to the distribution of factor returns and income inequality, a topic that has remained largely unexplored in this recent literature, which has instead focused on measurement issues, productivity effects and spillovers of intangibles (Corrado *et al.*, 2017). The model we develop also offers some insights on the role of capital deepening on structural change. In fact, we show that the capital-output ratio affects not only industries' labor share but also the relative importance of each sector in the economy. This issue has been pioneered by Acemoglu and Guerrieri (2008) but has been recently re-assessed by Liu (2012) and Alvarez-Cuadrado *et al.* (2018) for its implications for the labor share dynamics in the light of capital-labor substitution.

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 labor share. Finally, Section V concludes the paper.

# I Background

The decline of the labor share is global (Dao *et al.*, 2017) and has been documented for developed countries (O'Mahony *et al.*, 2019, Fukao and Perugini, 2018), 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 labor 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 labor share differ across studies. While increasing competition is generally associated with increasing labor shares (Bassanini and Manfredi, 2012), Azmat *et al.* (2012) show that the privatisation of network services is associated with a reduction in the labor share, as the focus of managers shifts away from employment targets and towards profitability targets. In the labor market, Blanchard and Giavazzi (2003) develop a model where the decline of the labor share is a short-run phenomenon led by a decrease in the bargaining power of unions. However, their model predicts that the labor share increases in the long-run, due to the interaction between product and labor market regulations, although no such increase is apparent in the data. Recent evidence shows that labor market reforms aimed at weakening labor protection are positively correlated with the labor share's decline (Ciminelli *et al.*, 2018), whilst policies promoting workers' reallocation are likely to increase the labor 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 labor and product market regulations need to be carefully modelled (Fiori *et al.*, 2012). Empirically, institutional settings do not present large variation 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 impacts of regulations on the labor share remains unknown. However, the downward trend of the labor share appears to be very persistent, with little difference across countries with varying institutional arrangements (O'Mahony *et al.*, 2019). This suggests that institutions may not be primarily responsible for the decline in the labor 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 labor share and increased import competition in the US. Conversely, results in 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 labor share. Similarly, Autor *et al.* (2017a) document that the decline of the labor 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 labor share, promoting greater movement of individuals, ideas and information contribute to its increase. However, the size of the estimated effects are rather small and not always significant.

The role of technological 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 labor 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, 2016, and 2017), 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 labor share has spread to high skilled occupations characterized by significant amounts of routine work, especially in the post-2000s.

Technical change may have also contributed to the decline of the labor share by a more subtle channel, as the adoption and diffusion of digital technologies has strengthened network effects, facilitating the rise of highly concentrated 'superstar' firms. Autor *et al.* (2017b) cite evidence that the decline in the labor share is not apparent within firms but only between firms. The focus on market power and rising profits is supported by empirical evidence in Dixon and Lim (2018) and in Barkai (2016) who highlights the decline in both the labor share and the capital share, while a larger amount 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. In turn, some intangible assets, such as those related to brand development, can reinforce the trend towards more concentrated firms and raise profits.

A related research effort focuses on the measurement of factor inputs and their corresponding labor share. For instance, Koh *et al.* (2018) claim that capitalisation of intellectual property products (IPP) in national accounts may help to explain a large portion of the labor share's decline in the United States. Cho *et al.* (2017) contend that the fall in the labor share is due to increased capital depreciation, and the share of labor 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 labor 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 labor'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 labor share in opposing directions, as some may substitute, and others may complement workers. Heterogeneous capital is central to research on the determinants of productivity, with earlier work concentrating on ICT and recent papers on intangible assets.[1] Less is known about how heterogeneous capital affects the labor share. The main objective of this paper is to investigate this issue.

## II Theoretical Framework

In this section we develop a baseline set-up which we use as guidance in the interpretation of the econometric results. Let us consider a static, multi-sector economy with aggregate output, $Y$, defined as 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 labor inputs of different types, $K_i$ and $L_i$. We could think of one sector as high tech ($I$), using, for example, innovative capital (ICT or intangible assets) and high skilled labor, and the other sector as low tech using traditional capital (non-ICT or tangible assets) and low skilled labor ($N$). 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

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

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 ($A_L > 0$ and $A_K > 0$):

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

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 labor 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 labor 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 $\tilde{k}_i = K_i/Y_i$, the labor 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 labor 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 labor share is a weighted average of industry labor shares, in which the industry shares are defined as the ratio between the value of industry and total output, $\theta_i = P_i Y_i / (\sum_i P_i Y_i)$:

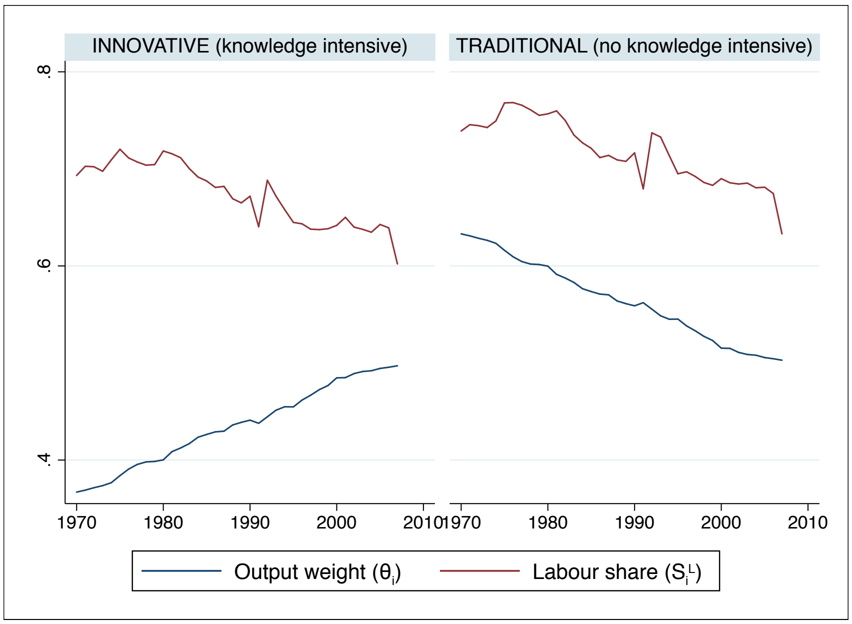
$$S^L = \frac{\sum_i W_i L_i}{PY} = S_I^L \theta_I + S_N^L \theta_N. \tag{6}$$

As a consequence, when an industry increases its capital-output ratio the effect on the economy-wide labor share is a combination of two effects, *within* and *between* (Karabarbounis and Neiman, 2014):[2]

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

The former is a first-order effect reflecting the change of the industry labor 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) labor share (see Acemoglu and Guerrieri, 2008). This effect reflects the change in the industry relative size and the gap in the sectoral labor shares (*between effect*). The within-effect is negligible when the industry share on GDP, $\theta_I$, tends to zero, whilst the between-effect is irrelevant when the labor share is equal among sectors.

Figure 1: Industry labor 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. Labor share ($S_i^L$) is the ratio between labor 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).

To gain insights on the sectoral sources of the labor share dynamics at an aggregate level, Figure 1 plots the evolution of the labor share and the share of industry output on GDP for innovative (knowledge intensive) and traditional (non-knowledge intensive) sectors, for our sample of OECD countries (see Sections III.1 and IV for details).[3] The group of innovative industries includes high-tech manufacturing sectors and knowledge intensive services, whilst the group of traditional industries collects all remaining sectors (Eurostat classification). Figure 1 shows that innovative industries are more capital intensive and have a lower labor 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 labor share should change as a result of capital deepening in the light of our model's predictions (see Table 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 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 is negative. In economic terms, these findings can be rationalised as follows. When goods are *substitutes* ($\epsilon < 0$ – CASE B.1) or *weak complements* ($\epsilon > 0$ but with low values – CASE B.2), $\theta_I$ increases with $\tilde{k}_I$. 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 (i.e. when $\epsilon > 0$ with low values). This manifests when the real output ratio $Y_I/Y$ is relatively low, i.e. below the threshold $\phi_I^{1/\epsilon}$. Conversely, when goods are *strong complements* ($\epsilon > 0$ with large values – CASE B.3), the increase in $Y_I$ is accompanied by a rise in the relative price, reducing the share of the sector in GDP. This occurs when $Y_I/Y$ is relatively high, i.e. above the threshold $\phi_I^{1/\epsilon}$.[4]

Summing up, our model shows that the impact of capital deepening on the aggregate labor share is ambiguous as it depends on the combination of the within- and the between-effect. However, at the industry level, the effect of an increase in the capital-output ratio is less ambiguous as it strictly reflects the degree of factors' substitutability. The model therefore allows for the possibility that some capital inputs may substitute and others may complement labor.

Table 1: Aggregate labor 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 | $> 0$ | $Y_I/Y > \phi_I^{1/\epsilon}$ | $< 0$ |

# 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 labor share (eq. 4), expressed in logs, using panel data for an industry-by-country sample:

$$\ln S_{ijt}^L = \alpha_{0ij} + \alpha_{1ij} \ln A_{ijt} + \alpha_2 \ln \tilde{k}_{ijt} + \epsilon_{ijt} \tag{9}$$

where $A$ is capital-specific technical change and $\tilde{k}$ is the capital-output ratio, where output is measured by industry value added. Subscript $i$ denotes industries and $j$ countries, $\alpha_{0ij}$ are industry-country fixed effects and $\epsilon_{ijt}$ is a spherical error term. If labor and capital are gross substitutes the coefficient of capital intensity is expected to be negative ($\alpha_2 < 0$), and positive if factor inputs are complement ($\alpha_2 > 0$). $A$ is not observable but can be proxied by TFP, implying that the sign of this parameter should follow that of the capital-to-output ratio (Bassanini and Manfredi, 2012).[5]

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

$$\ln S_{L,ijt} = \beta_{0ij} + \beta_{1ij} \ln S_{L,ijt-1} + \beta_{2ij} \ln A_{ijt} + \beta_{3ij} \ln A_{ijt-1} + \beta_{4ij} \ln \tilde{k}_{ijt} + \beta_{5ij} \ln \tilde{k}_{ijt-1} + \epsilon_{ijt} \tag{10}$$

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

$$\Delta \ln S_{L,ijt} = \gamma_{0ij} + \gamma_{1ij}\Delta \ln A_{ijt} + \gamma_{2ij}\Delta \ln \tilde{k}_{ijt} + \gamma_{3ij} \ln S_{L,ijt-1} + \gamma_{4ij} \ln A_{ijt-1} + \gamma_{5ij} \ln \tilde{k}_{ijt-1} + \epsilon_{ijt} \tag{11}$$

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: $\alpha_{2ij} = -\gamma_5/\gamma_3$, whose significance is checked using the non-linear test of the delta method. The coefficient $\gamma_3$ 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. 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 knowledge capital.

We estimate equation (11) using data from the EU KLEMS dataset (release 2009). This data set covers seventeen OECD countries and twenty market industries (12 manufacturing and 8 service industries), spanning from 1970 to 2007.[6] The exclusion of the latest years after the financial turmoil allows us to isolate the long-run impact of technological factors from the effect of the crisis. The EU KLEMS dataset provides information on industry accounts (labor compensation, value added, capital stocks with a division into ICT and non-ICT components) and derived variables such as TFP.[7] Levels of TFP are measured in relative terms, with values for US industries in 1997 as numeraire. Capital measures are obtained using the perpetual inventory method and geometric depreciation. All monetary variables are made comparable using the relative PPP of industry output (1997 base), following Inklaar and Timmer (2008). We proxy knowledge capital using the cumulative value of R&D expenses (source: OECD ANBERD 2002 and 2006). Similar to the other capital assets, we express knowledge capital relative to real value added. Knowledge capital is built by means of the perpetual inventory method assuming an annual geometrical depreciation rate of 15%. R&D expenses are expressed at constant prices and converted into an industry base of PPP (base year=1997). The value of capital stock at the initial year is computed with the formula devised by Hall and Mairesse (1995). Appendix Tables A.1 and A.2 present summary statistics at the country and industry level.

Table 2: Capital-labor substitutions and technology impact on labor shares (long-run coefficients)

| | Homogeneous coefficients | Heterogeneous AMG coefficients | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| TFP | -0.187*** | -0.395*** | -0.457*** | -0.372*** |
| | (0.032) | (0.034) | (0.053) | (0.061) |
| Total capital/value added | -0.010 | -0.070** | | |
| | (0.023) | (0.028) | | |
| Non-ICT capital/value added | | | -0.022 | -0.003 |
| | | | (0.049) | (0.062) |
| ICT capital/value added | | | -0.037*** | -0.045*** |
| | | | (0.007) | (0.012) |
| Knowledge capital/value added | | | | 0.052** |
| | | | | (0.021) |
| ECM | -0.134*** | -0.515*** | -0.632*** | -0.750*** |
| | (0.005) | (0.020) | (0.023) | (0.03å0) |
| Obs | 8620 | 8620 | 8620 | 5348 |
| Groups | 340 | 340 | 340 | 207 |

**Notes:** Dependent variable is the labor share over 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 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). *, **, *** significant at 10, 5 and 1% respectively. The reduction in the number of observations is column (4) is due to missing observations for R&D, especially for services sectors.

### III.2 Baseline results

Table 2 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(1,1,1). Results for a richer dynamic specification, ARDL(2,2,2), are presented in Appendix Table A.3. In the first column of Table 2, 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) and (3) we relax this assumption and present estimates based on an augmented mean group 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 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).

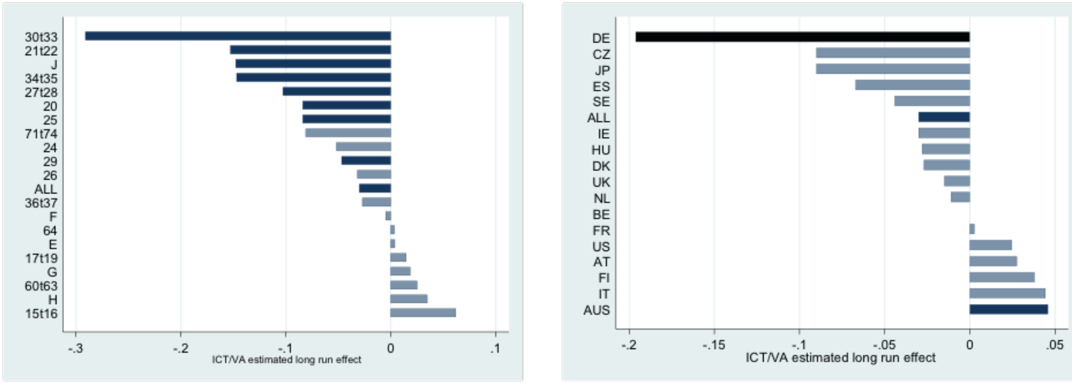
Results in Table 2 reveal that the impact of TFP is always negative and statistically significant, in line with earlier studies (Bassanini and Manfredi, 2012, Bentolila and Saint-Paul, 2003). Given that these are long-run coefficients, they represent the trend impact of TFP, and can be considered as a proxy for exogenous technical progress. The negative impact of technology is larger when we relax the assumption of homogeneous coefficients (columns 2 and 3). Our results confirm the presence of capital-labor substitution, as the coefficient estimate for the total capital to value added ratio is negatively signed, and significant when we allow for heterogeneous coefficients. These results suggest that there is large heterogeneity across industries in the effect of technology and the capital-output ratio and failing to account for this issue may lead to severely biased estimates. The error correction term has the expected sign and it is always statistically significant, supporting our modelling framework.

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-labor substitution is driven by ICT 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 labor 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 labor share. ICT capital assets have spread massively 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). A more recent literature has shown that the fast diffusion of ICT and the proliferation of information-intensive goods, software platform and online services, has created the conditions for high industry concentration (Autor *et al.*, 2017b), which has been linked to declining labor (and capital) shares (Barkai, 2016). 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 unchanged our main results. 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 adding an additional form of capital asset: knowledge capital. When we introduce knowledge capital we look at the impact of technology in more detail and we are able to distinguish between exogenous technology (as captured by TFP) and the source of endogenous technological change, measured by the industry' own decision to invest in innovation. Knowledge-generating activities increase the degree of firm competitiveness and, therefore, are unlikely to adversely influence labor share dynamics. Indeed, technologically advanced industries are characterized by a more dynamic demand, suffer less cost-cutting pressure and have larger rents to share with workers (Aghion *et al.*, 2017). Also, more innovative firms employ

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.

higher skilled or highly educated workers to manage processes of technology production, adaptation and implementation (Mason *et al.*, 2019). From this perspective, knowledge capital may work differently from those assets considered previously, ICT and non-ICT capital. The introduction of knowledge capital does not change our conclusions for ICT and non-ICT capital and TFP; however, and consistent with our expectations, the relationship between this asset type and the labor share is profoundly different as knowledge capital contributes to an increase of the labor share. This suggests that investments in innovative activities complement, rather than substitute, labor.

We now investigate the role of ICT and TFP in driving the decline of the labor share, by re-estimating the specification in column 3 for each industry and each country. 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 colour 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 labor share by approximately 0.3%. At the country level, the effect of ICT/VA is only significant in two countries, Germany and Austria. Interestingly, these two countries are positioned at the two extreme points of the distribution, with Germany displaying the largest negative effect and Austria the largest positive effect. These results show that ICT capital intensity is a driver of labor share dynamics between industries, but it only marginally affects differences across countries. This strongly posits in favour of the fact that the decline in the labor share is driven by changes in technological conditions of production and less by changes in the

Figure 3: Long-run coefficient estimates of TFP, by industry and country (baseline estimates)

(A) (B)


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

institutional settings governing the functioning of product and factor markets.

Figure 3 shows the long-run coefficient estimates for TFP, at the industry and country level. The general impact of technology is negative and statistically significant in all industries with a particularly large coefficient in the network industries (E). The impact of TFP is always negative and significant in most countries; there is quite a lot of variation in the size of the effect, which ranges between -0.35 (Netherlands) and -0.824 (Spain).

Overall, these results give partial support to previous work by Bentolila and Saint-Paul (2003) and Karabarbounis and Neiman (2014), who claim that industry variations in labor 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. However, other technological factors, embedded in TFP, have a pervasive effect both at the industry and country level and this is hard to reconcile with the assumption that only industry variations matter.

### III.3 Predicting the labor share decline

In this section we answer the question of how well our model can predict the long-run changes in the labor share, using the estimates reported in columns (3) and (4) of Table 2. We disentangle the observed rate of change in the labor share into *predicted* and *residual* effects using a simplified shift-and-share decomposition model, which is broadly consistent with our theoretical framework in Section II. Assuming discrete time for simplicity of notation, the rate of change in the labor share at country level can be written as (country subscript $j$ omitted):

$$\frac{\Delta S_t^L}{S_t^L} = \underbrace{\sum_{i=1}^{n} \frac{\widehat{\Delta S_{it}^L}}{S_{it}^L} \bar{\theta}_i}_{predicted\ effect} + \underbrace{\sum_{i=1}^{n} \bar{S}_i^L \frac{\Delta \theta_{it}}{\theta_{it}}}_{residual\ effect} \tag{12}$$

where $\Delta$ is the first-year difference operator, and the bar denotes the value of the variable at the beginning of the sample year. $n$ is the number of industries in each country. $\theta_i$ is the industry share of GDP whereas $S_i^L$ is the labor share at the level of individual sector. The total change in industry labor share predicted by our model is computed as:

$$\frac{\widehat{\Delta S_{it}^L}}{S_{it}^L} = \sum_p \hat{\gamma}_i^p \frac{\Delta x_{it}^p}{x_{it}^p}.$$

$x^p$ are the regressors used in the labor share equation. In the baseline estimation, the set $x^p$ includes $TFP$, ICT capital-value added ratio, and non-ICT capital-value added. In the regression extended to include knowledge capital, $x^p$ also includes the ratio between the R&D stock and value added.

In Table 3, the first column reports the cumulative change in labor share for our sample of countries and the aggregate. Average values are computed as weighted means of country-specific figures, where we use as weight the share of each country in terms of relative GDP obtained using industry PPP for value added (Inklaar and Timmer, 2008).

In the overall sample, the labor share declined by 11.1% cumulatively since the early 1970s (col. A). Our baseline empirical model would predict a fall in labor share by 14.9% (col. B), somewhat over-fitting the observed change. This would imply a positive (residual) (col. C). Our model overstates the decline in nine countries, but in many cases the residuals are very small. A similar pattern of results emerges for the regression extended to include knowledge capital (col. D). However, the residual component tends to be much larger, suggesting that R&D may not be fully capturing knowledge inputs. This leads to our next analysis which considers a broader definition of intangible assets.

# IV Labor 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

Table 3: Explained LS variation in the long run

| | Observed cumulative change in LS (A) | Baseline model (col. 3, Table 2) (predicted) (B) | (residual) (C) | Extended model with R&D (col. 4, Table 2) (predicted) (D) | (residual) (E) |
|---|---|---|---|---|---|
| AT | -0.269 | -0.173 | -0.096 | . | . |
| AU | -0.186 | -0.128 | -0.058 | -0.157 | -0.029 |
| BE | -0.074 | -0.121 | 0.048 | . | . |
| CZ | -0.020 | -0.029 | 0.009 | . | . |
| DE | -0.098 | -0.139 | 0.041 | -0.090 | -0.008 |
| DK | -0.119 | -0.033 | -0.087 | -0.263 | 0.143 |
| ES | -0.102 | -0.221 | 0.119 | -0.822 | 0.720 |
| FI | -0.236 | -0.249 | 0.013 | -0.387 | 0.151 |
| FR | -0.021 | 0.078 | -0.099 | -0.225 | 0.205 |
| HU | -0.079 | -0.209 | 0.130 | . | . |
| IE | -0.168 | -0.230 | 0.062 | 0.043 | -0.210 |
| IT | -0.124 | -0.217 | 0.092 | -0.612 | 0.488 |
| JP | -0.086 | -0.288 | 0.202 | -0.249 | 0.163 |
| NL | -0.212 | -0.210 | -0.002 | -0.236 | 0.024 |
| SE | -0.085 | 0.105 | -0.190 | -0.204 | 0.119 |
| UK | 0.099 | -0.123 | 0.222 | 0.202 | -0.103 |
| US | -0.105 | -0.170 | 0.065 | -0.060 | -0.045 |
| TOTAL | -0.111 | -0.149 | 0.038 | -0.170 | 0.059 |

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, mineral exploration and new product development costs in the financial 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,[8] adding these assets to the analysis of the labor 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. When including intangible assets, the labor share equation is re-formulated as follows:

$$\ln S^*_{L,ijt} = \alpha_{0ij} + \alpha_{1ij} \ln A^*_{ijt} + \alpha_2 \ln \tilde{k}^*_{ijt} + \alpha_3 \ln \tilde{kint}^*_{ijt} + \epsilon_{ijt} \tag{13}$$

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 value added. 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). Note in our main database, EU KLEMS, software, mineral exploration and artistic originals are already included in the estimates and so they are not part of intangible capital (*kint*). 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 intangible affect the labor shares in different ways. As discussed above, innovative property has impacts on the extent of competition firms face, as well as being intensive in the use of skilled labor. As before, we expect this to be positively related to the labor 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) we expect them to have a negative impact on the labor share.

## IV.1 Econometric strategy

Estimates of intangible assets at the industry level for EU countries are taken from Niebel *et al.* (2016). These data span from 1995 to 2007 - Appendix Tables A4 and A5 present summary statistics. The shorter time dimension in this section, compared to the data used in Section III, prevents the use of dynamic panel techniques. Therefore, in this section we adopt a Fixed Effect (FE) estimator to control for cross-sectional heterogeneity and first order serial correlation (Prais and Winsten, 1954). 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 labor share is anti-cyclical because of labor market rigidities and labor 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 also 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 labor cost shares. In this case, causality would run from the labor share to capital-output ratios. In the first part of the paper the long-run effects are estimated with the use of the dynamic specification and adjusting for cross sectional dependence, as outlined above. 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 incentives to purchase capital assets internally, compared to acquiring the corresponding capital services externally. In both cases, the firm's decision is likely to be determined by 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). On this basis, we instrument ICT capital using time-varying indicators reflecting the extent of telecom service regulation in force at home and abroad.We constructed two sets of indicators, one reflecting regulations within the country and the other based on regulations abroad. Only the latter proved to be valid instruments based on standard tests. In a similar way, to predict variation in intangible investments, we look at the regulation, which implicitly affects the cost of these investments, compared to the purchases of the corresponding service on the market. For this reason, we instrument innovative intangibles with the regulation of architect and engineering professional services (which is a close substitute for internal R&D). For economic competencies, we consider the regulation of legal and accounting professional services. Data on service regulation come from OECD Sector Regulation Indicators (see Koske *et al.*, 2015).

Since these indicators are country specific (and time varying), 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). Inter-industry intermediates transactions come from the WIOD database.[9]

Table 4: The impact of intangible assets on labor share, 1995-2007 (FE-OLS estimates)

| | Total LS | | Low/inter-mediate skilled LS | High-skill LS |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| TFP - trend | -0.209*** | -0.185*** | -0.271*** | 0.316*** |
| | (0.027) | (0.027) | (0.031) | (0.049) |
| TFP - cycle | -0.578*** | -0.536*** | -0.509*** | -0.306*** |
| | (0.030) | (0.031) | (0.036) | (0.057) |
| Non-ICT capital/Value added | 0.000 | -0.003 | 0.065** | 0.056* |
| | (0.022) | (0.022) | (0.026) | (0.033) |
| ICT capital/Value added | -0.0125*** | -0.0132*** | -0.071*** | 0.166*** |
| | (0.004) | (0.004) | (0.004) | (0.008) |
| Intangibles /Value added | -0.034*** | | | |
| | (0.012) | | | |
| Innovative properties/Value added | | 0.064*** | 0.093*** | -0.023 |
| | | (0.018) | (0.021) | (0.031) |
| Economic Competencies /Value added | | -0.046*** | -0.072*** | 0.095*** |
| | | (0.017) | (0.020) | (0.031) |
| Groups | 300 | 300 | 300 | 300 |
| Observations | 4120 | 4120 | 4120 | 4120 |
| R-squared | 0.902 | 0.900 | 0.982 | 0.912 |

**Notes:** Dependent variable is the total labor share over value added. Robust standard errors in parentheses. *, **, *** significant at 10, 5 and 1% respectively.

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

Table 4 shows the results based on the estimation of equation (13), 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). The impact of TFP turns out to be negative and statistically significant, while the coefficient of non-ICT capital over value added never achieves standard levels of statistical significance, in line with estimates in Table 2. ICT capital contributes significantly to the decline of the labor share. Similarly, intangible assets show an overall negative impact on the labor share, but with an elasticity which is approximately twice as large as that of ICT capital, testifying to the importance of this latest wave of innovative assets in explaining the labor share.

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 2, as they positively affect the labor share.

In the last two columns we present estimates of equation (13) for the two groups of workers, low/medium skilled (column 3) and highly skilled (column 4). Results for the medium and low skilled workers are mostly in line with those for the overall sample: negative and significant impact of TFP, ICT capital and economic competencies. Overall, this suggests that new technologies are playing an important role in driving the decline of the labor share of the low skilled. However, we also find that innovative properties contribute to an increase in their labor share. This suggests that firms investing in innovations create opportunities for improving conditions of a wider group of workers. This result is consistent with the analysis in Aghion *et al.* (2017), 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 5: The impact of intangible assets on labor share, 1995-2007 (IV-2SLS estimates)

| | | IV-2SLS | |
|---|---|---|---|
| | Total LS | Low/intermediate skilled LS | Skilled LS |
| TFP - trend | -0.363*** | -0.465*** | 0.046 |
| | (0.098) | (0.134) | (0.183) |
| TFP - cycle | -0.684*** | -0.723*** | -0.473** |
| | (0.103) | (0.140) | (0.192) |
| Non-ICT capital/Value added | 0.0280 | 0.1016* | 0.120** |
| | (0.035) | (0.053) | (0.051) |
| ICT capital/Value added | 0.014 | -0.060*** | 0.219*** |
| | (0.011) | (0.016) | (0.023) |
| Intangibles/VA | | | |
| Innovative properties/Value added | 0.045 | 0.236 | -0.589*** |
| | (0.119) | (0.154) | (0.216) |
| Economic competencies/Value added | -0.318*** | -0.532*** | 0.198 |
| | (0.087) | (0.121) | (0.173) |
| Groups | 300 | 300 | 300 |
| Observations | 3580 | 3580 | 3580 |
| Hansen J test | 0.489 | 0.405 | 0.404 |
| ($p$-value) | [0.484] | [0.525] | [0.525] |
| Kleibergen-Paap LM statistic | 54.9 | 49.6 | 54.9 |
| ($p$-value) | [0.000] | [0.000] | [0.000] |

**Notes:** Dependent variable is the total labor share over value added. Standard errors robust to heteroskedastictity and auto-correlation in parentheses. Instruments used: foreign regulation of telecom services, legal and accounting services, architect and engineering services. *, **, *** significant at 10, 5 and 1% respectively.

Results for the highly skilled interestingly show a different pattern of effects. Technical change complements

Table 6: Explained LS variation in the short term

| | (A) Observed variation in LS (cumulative change) | (B) Predicted impact (within effect) | (C=A × B) Explained variation |
|---|---|---|---|
| TFP - trend | 0.149 | -0.185 | -0.028 |
| TFP - cycle | 0.008 | -0.536 | -0.004 |
| Non-ICT capital /Value added | -0.104 | 0.000 | 0.000 |
| ICT capital /Value added | 1.022 | -0.013 | -0.013 |
| Innovation/Value added | 0.211 | 0.064 | 0.014 |
| Econ. competencies/Value added | 0.332 | -0.046 | -0.015 |
| TOTAL | - | - | -0.046 |
| Observed LS | - | - | -0.067 |
| Total explained (%) | - | - | 68.7 |
| Unexplained residual (% ) | - | - | 31.3 |

**Notes:** Column A reports the cumulative change of the variables. Column B reports the coefficients estimated for the explanatory variables from col. 2, Table 4. Column C reports explained variation in LS due to each factor.

this group of workers, as suggested by the positive coefficient found for TFP, ICT capital and economic competences. However, we do not find any effect of innovative properties on the labour share of the highly skilled. It is possible that, our skills measure, which only relies on education, does not fully capture workers' abilities (Chevalier and Lindley, 2009).

Table 5 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 labor share. Similarly, coefficient estimates for low/intermediate skilled labor are broadly consistent with the results in Table 4, 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 4, col. 3) to -0.532 (Table 5, 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 5 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).

The negative effect of innovative properties assets on the labor share of the high-skilled may be explained with the fact that these investments lead to introducing 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 labor share might indicate that companies spending more on R&D workers seek to save on labor costs for similarly skilled groups of workers, operating outside the R&D department. Moreover, following Aghion *et al.* (2017), 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 labor 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. As a further robustness check, Appendix Table A.7 presents results based on a standard GMM regression, where we use lagged values of the endogenous variables as instruments (maximum of two lags). Here, there are fewer surprises as results confirm the overall story and the size of the effect of intangible assets are consistent with those presented in Table 4.

Finally, we examine the predictive capacity of our empirical results and show which proportion of the observed variation in the LS can be explained by our estimates. Here we more simply quantify the variation in the LS explained by the static estimates for the period from 1995 to 2007, based on the results from column 2 of Table 4. The results in Table 6 show that over two thirds of the variation in the labor share is explained by our specification.

# V Conclusions

This study provides a novel contribution to the debate on the causes of the decline of the labor share, by focusing on the different types of capital assets used by firms. Previous analyses did not explore the possibility that capital and labor can be substitutes or complements depending on the nature of capital. Overall, we find that both ICT capital assets and economic competencies decreases the labor 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 labor 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 labor. 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 exogenous technology, as captured by TFP, ICT capital and intangible assets capturing economic competencies. In contrast, intangible capital capturing innovative activities appears to promote the increase in the labor 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. In this context, measuring the different types of capital becomes crucial. Recent debate on the nature of intangibles has identified some problematic issues. For example, in the case of intellectual properties, globalisation leads to a divergence between ownership and use across national borders. Current intangibles datasets do not account for these aspects, as they are generally based on aggregate data. There is an urgent need for statistical offices to develop better measures of intangible assets, building up from firm level data.

Finally, this paper links with recent literature questioning what is captured by profits when they are calculated as a residual between output and current expenditures. As intangible assets are not generally measured in official datasets, it is difficult to disentangle whether increases in profits are due to firms' returns on their intangible investments or above normal profits due to market concentration. The superstar firm literature emphasises that markets have become less competitive due to the nature of the recent digital technology revolution. The same technological developments, however, have led to increased investment in intangible capital as complementary inputs. In turn, investment in intangible assets, such as brand development, might reinforce any trend towards concentration. Disentangling these influences is an important area for future research.

## Notes

[1]Examples using the growth accounting approach are Jorgenson and Stiroh (2000), Oliner and Sichel (2000), Timmer *et al.* (2010), and using econometric estimation are O'Mahony and Vecchi (2005) and Venturini (2009). Recent work highlighting the increasing role of intangible capital in explaining productivity growth in advanced economies includes Corrado *et al.* (2017); Niebel *et al.* (2016) and in driving investment demand (Alesina *et al.*, 2005; Cette *et al.*, 2017).

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

[3]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).

[4]As a relevant special case, when $\epsilon = 0$, aggregate output is combined as a Cobb-Douglas technology and the between-effect vanishes.

[5]In a more general CES specification, technical change would have neutral and factor specific components. It implies that the impact estimated for technical progress from equation (9) would be the product of capital augmenting and Hicks neutral technical progress. This interpretation for $\alpha_1$ looks plausible as estimates of TFP from EU KLEMS are based on a translog production function assuming Hicks neutral technical change.

[6]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)

[7]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. It does not include Research and Development capital which was added to the national accounts at a later date. A general overview on this dataset can be found in O'Mahony and Timmer (2009).

[8]Most of these assets 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. 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.

[9]World Input-output database, available at www.wiod.org.

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# Appendix Tables

TABLE A.1. - SUMMARY STATISTICS AT COUNTRY LEVEL, 1970-2007

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

TABLE A.2. - SUMMARY STATISTICS AT INDUSTRY LEVEL, 1970-2007

| | Labor share | Non- ICT capital/ Value added | ICT capital/ Value added | R&D capital/ Value added | TFP |
|---|---|---|---|---|---|
| Food | 0.62 | 0.55 | 0.02 | 0.06 | 0.90 |
| Textiles | 0.81 | 0.61 | 0.02 | 0.05 | 0.58 |
| Wood | 0.76 | 0.49 | 0.02 | 0.02 | 0.91 |
| Paper | 0.68 | 0.48 | 0.05 | 0.03 | 0.82 |
| Chemicals | 0.53 | 0.63 | 0.02 | 0.53 | 1.46 |
| Rubber | 0.71 | 0.36 | 0.01 | 0.11 | 2.08 |
| Non-met. min. | 0.68 | 0.48 | 0.02 | 0.08 | 1.42 |
| Basic metals | 0.70 | 0.50 | 0.02 | 0.07 | 0.90 |
| Machinery, nec | 0.75 | 0.26 | 0.02 | 0.21 | 0.92 |
| Electr. Eq. | 0.73 | 0.46 | 0.06 | 0.68 | 0.88 |
| Transp. Eq. | 0.77 | 0.77 | 0.06 | 0.41 | 0.40 |
| Mauf., nec | 0.88 | 0.25 | 0.02 | 0.05 | 1.28 |
| Transport | 0.73 | 0.54 | 0.05 | 0.01 | 0.73 |
| Post, telecom | 0.55 | 0.40 | 0.11 | 0.05 | 1.11 |
| Business serv. | 0.76 | 0.40 | 0.10 | 0.08 | 0.62 |
| Ulities | 0.37 | 1.86 | 0.05 | 0.04 | 0.53 |
| Construction | 0.82 | 0.14 | 0.01 | 0.01 | 0.96 |
| Wholesale, retail | 0.75 | 0.26 | 0.03 | 0.02 | 1.10 |
| Hotels | 0.86 | 0.53 | 0.03 | . | 0.65 |
| Fin. Interm. | 0.59 | 0.29 | 0.06 | 0.02 | 1.16 |
| Total average | 0.70 | 0.51 | 0.04 | 0.15 | 0.97 |

TABLE A.3. - CAPITAL-LABOR SUBSTITUTIONS AND TECHNOLOGY IMPACT ON LABOR SHARES

LONG-RUN COEFFICIENTS – ARDL(2,2,2)

| Explanatory variables | Homogeneous coefficients | Heterogeneous Coefficients AMG | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Total Factor Productivity (TFP) | -0.175*** | -0.317*** | -0.387*** |
| | (0.000) | (0.000) | (0.000) |
| Total capital/ value added | -0.002 | -0.047 | |
| | (0.973) | (0.118) | |
| Non-ICT capital/value added | | | -0.058 |
| | | | (0.302) |
| ICT capital/ value added | | | -0.022*** |
| | | | (0.003) |
| ECM | -0.139*** | -0.641*** | -0.664*** |
| | (0.000) | (0.000) | (0.000) |
| Obs | 8,280 | 8,280 | 7,580 |
| Groups | 340 | 340 | 340 |

**Notes**: Dependent variable is the labor share over value added. p-values in brackets (obtained with delta method). Columns (1) reports results for an ECM model with homogeneous parameters. Columns (2) and (3) are augmented mean group

TABLE A.4. - SUMMARY STATISTICS FOR THE 1995-2007 DATASET- BY COUNTRY

| Country | AT | BE | CZ | DE | DK | ES | FI | FR |
|---|---|---|---|---|---|---|---|---|
| Labor share | 0.576 | 0.613 | 0.545 | 0.679 | 0.651 | 0.601 | 0.600 | 0.635 |
| TFP | 1.171 | 1.054 | 1.125 | 1.094 | 0.992 | 0.971 | 1.164 | 1.146 |
| Non-ICT capital/ VA | 0.026 | 0.032 | 0.003 | 0.003 | 0.008 | 0.013 | 0.056 | 0.006 |
| ICT capital/VA | 0.095 | 0.082 | 0.006 | 0.005 | 0.026 | 0.024 | 0.105 | 0.009 |
| Intangibles capital/VA | 0.268 | 0.300 | 0.204 | 0.316 | 0.270 | 0.166 | 0.311 | 0.310 |
| Innovative properties/VA | 0.181 | 0.185 | 0.128 | 0.227 | 0.175 | 0.094 | 0.204 | 0.202 |
| Economic comp./VA | 0.067 | 0.092 | 0.058 | 0.076 | 0.085 | 0.054 | 0.086 | 0.084 |
| | HU | IE | IT | JP | NL | SE | UK | US |
| Labor share | 0.594 | 0.576 | 0.644 | 0.573 | 0.621 | 0.616 | 0.666 | 0.591 |
| TFP | 1.334 | 1.106 | 1.007 | 1.010 | 1.091 | 1.139 | 1.062 | 1.077 |
| Non-ICT capital/ VA | 0.001 | 0.147 | 0.006 | <0.001 | 0.027 | 0.004 | 0.008 | 0.001 |
| ICT capital/VA | 0.001 | 0.413 | 0.011 | <0.001 | 0.069 | 0.006 | 0.022 | 0.002 |
| Intangibles capital/VA | 0.203 | 0.151 | 0.187 | 0.312 | 0.276 | 0.370 | 0.281 | 0.343 |
| Innovative properties/VA | 0.086 | 0.078 | 0.125 | 0.266 | 0.155 | 0.251 | 0.125 | 0.213 |
| Economic comp./VA | 0.093 | 0.062 | 0.053 | 0.046 | 0.097 | 0.091 | 0.141 | 0.100 |

TABLE A.5. - SUMMARY STATISTICS FOR THE 1995-2007 DATASET - BY INDUSTRY

| Industry | 15t16 | 17t19 | 20 | 21t22 | 24 | 25 | 26 | 27t28 | 29 | 30t33 |
|---|---|---|---|---|---|---|---|---|---|---|
| Labor share | 0.555 | 0.744 | 0.694 | 0.590 | 0.379 | 0.602 | 0.588 | 0.655 | 0.657 | 0.576 |
| TFP | 1.001 | 1.083 | 1.117 | 1.092 | 1.074 | 1.155 | 1.078 | 1.051 | 1.099 | 1.451 |
| Non-ICT capital/ VA | 0.009 | 0.040 | 0.068 | 0.012 | 0.010 | 0.042 | 0.031 | 0.017 | 0.028 | 0.009 |
| ICT capital/VA | 0.020 | 0.086 | 0.196 | 0.038 | 0.022 | 0.077 | 0.090 | 0.028 | 0.036 | 0.017 |
| Intangibles capital/VA | 0.232 | 0.196 | 0.142 | 0.178 | 0.868 | 0.378 | 0.263 | 0.199 | 0.352 | 0.522 |
| Innovative properties/VA | 0.126 | 0.092 | 0.062 | 0.080 | 0.747 | 0.286 | 0.183 | 0.119 | 0.248 | 0.414 |
| Economic comp./VA | 0.091 | 0.102 | 0.074 | 0.085 | 0.076 | 0.070 | 0.069 | 0.068 | 0.080 | 0.074 |
| | 34t35 | 36t37 | 60t63 | 64 | 71t74 | E | F | G | H | J |
| Labor share | 0.626 | 0.747 | 0.656 | 0.451 | 0.674 | 0.309 | 0.771 | 0.666 | 0.771 | 0.516 |
| TFP | 1.198 | 1.072 | 1.020 | 1.302 | 0.957 | 1.083 | 0.972 | 1.095 | 0.952 | 1.088 |
| Non-ICT capital/VA | 0.036 | 0.056 | 0.007 | 0.012 | 0.005 | 0.015 | 0.007 | 0.003 | 0.017 | 0.004 |
| ICT capital/VA | 0.146 | 0.147 | 0.019 | 0.021 | 0.012 | 0.068 | 0.018 | 0.007 | 0.039 | 0.011 |
| Intangibles capital/VA | 0.394 | 0.262 | 0.104 | 0.143 | 0.319 | 0.112 | 0.134 | 0.156 | 0.126 | 0.252 |
| Innovative properties/VA | 0.295 | 0.155 | 0.031 | 0.077 | 0.154 | 0.046 | 0.048 | 0.054 | 0.036 | 0.107 |
| Economic comp. /VA | 0.074 | 0.095 | 0.065 | 0.046 | 0.121 | 0.058 | 0.072 | 0.092 | 0.080 | 0.121 |

TABLE A.6

INSTRUMENTAL VARIABLE ESTIMATION. FIRST STAGE

| | Total Labour Share | | | Low & Interm. Skilled Labour Share | | | High-Skilled Labour Share | | |
|---|---|---|---|---|---|---|---|---|---|
| | ICT/VA | Innov. Prop./ VA | Economic comp. / VA | ICT/VA | Innov. Prop./ VA | Economic comp./ VA | ICT/VA | Innov. Prop./ VA | Economic comp./ VA |
| Foreign telecom services regulation, LN (t-1) | -0.447*** (0.020) | -0.002 (0.009) | -0.096*** (0.010) | -0.364*** (0.023) | -0.006 (0.011) | -0.101*** (0.012) | -0.447*** (0.020) | -0.002 (0.009) | -0.096*** (0.010) |
| Foreign legal and accounting services regulation, LN (t-1) | -0.382*** (0.111) | 0.097** (0.049) | 0.352*** (0.057) | -0.720*** (0.075) | 0.071** (0.034) | 0.186*** (0.035) | -0.382*** (0.110) | 0.097** (0.050) | 0.352*** (0.057) |
| Foreign architect and engineering services regulation, LN (t-1) | 0.065* (0.035) | -0.100*** (0.014) | 0.021 (0.014) | 0.064** (0.031) | -0.105*** (0.013) | -0.003 (0.013) | 0.065* (0.035) | -0.100*** (0.014) | 0.021 (0.014) |
| Total professional services regulation (weighted mean), LN (t-1) | -0.990*** (0.155) | -0.042 (0.062) | -0.323*** (0.076) | -1.137*** (0.111) | 0.019 (0.048) | -0.052 (0.056) | -0.990*** (0.155) | -0.042 (0.062) | -0.322** (0.077) |
| $R^2$ | | | | | | | | | |
| OBS | 3580 | 3580 | 3580 | 3580 | 3580 | 3580 | 3580 | 3580 | 3580 |
| Tests of excluded IV | | | | | | | | | |
| F(6, 3271), P value | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| Sanderson-Winmejer F(4, 3271), P value | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |

Notes. *Significant at 10% level; ** significant at 5% level; *** significant at 1% level. Robust standard errors are displayed in brackets.

TABLE A.7

GMM ESTIMATION (HANSEN 1982)

| VARIABLES | (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 |
| | (0.03) | (0.056) | (0.038) |
| Economic competencies/Value added | -0.062** | 0.129** | -0.085** |
| | (0.032) | (0.065) | (0.039) |
| | | | |
| Groups | 320 | 320 | 320 |
| Observations | 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. *Significant at 10% level; ** significant at 5% level; *** significant at 1% level. 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)