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# Assessing the Impact of New Technologies on Wages and Labour Income Shares

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# Abstract

This paper advances the literature on the impacts of new technologies on labour markets, focusing on wage and labour income shares. Using a dataset from 32 countries and 38 industries, we analyse the effects of new technologies – proxied by patents, information and communication technology (ICT) capital usage, and robot intensity – on average wages and labour income shares over time. Our results indicate a positive correlation between patents and wage levels along with a minor negative impact on labour income shares, suggesting that technology rents are not fully passed on to labour. Robot intensity is positively associated with labour income shares, while ICT capital has an insignificant effect. These effects persist over time and are reinforced by global value chain (GVC) linkages. Our conclusions align with recent research indicating that new technologies have a generally limited impact on wages and labour income shares.

Keywords: Robot adoption, ICT investment, new technologies, GVC, wages, labour income shares

JEL classification: C13, C23, F14, F16, O33

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# 1. Introduction

The transformative power of technology has long been a cornerstone of economic evolution, reshaping industries and labour markets. This study delves into the intricate dynamics between technological advances and their implications for wages and labour income shares, an issue accentuated by the Fourth Industrial Revolution. Our research draws on Johnson and Acemoglu's (2023) concept of the 'productivity bandwagon' associated with neoclassical economic theories, suggesting that technological progress should lead to productivity gains and improved average wages despite the potential for increased inequality. This view contends with the notion of 'so-so automation', according to which efficiency gains benefit a select few, potentially leaving the broader workforce adrift unless counteracted by strategic policies and robust labour institutions. In their book 'Power and Progress', Johnson and Acemoglu (2023) argue that the equitable distribution of technological benefits is not automatic. Instead, they contend that a deliberate societal choice to distribute these gains is required and therefore advocate for policies that empower workers against a monopolistic concentration of wealth. This perspective informs our evaluation of global technological innovations – such as patents, information and communication technology (ICT) capital, and robot intensity – on wage levels and labour income shares, drawing upon a comprehensive dataset spanning 38 sectors across 32 countries over the 1996-2017 period.

The literature on the impact of new technologies, automation and digitalisation on employment and wages is extensive, yet inconclusive. Views range from a dystopian future of reduced labour demand (Frey and Osborne 2017) to more optimistic outlooks in which technology complements human labour (Autor 2015; Acemoglu and Restrepo 2017). While recent discussions veer away from a jobless future (OECD 2019; Stehrer 2019; World Economic Forum 2018), the empirical assessment of technology's effects on different types of labour remains essential. Studies indicate limited impacts on overall employment (Antón et al. 2022; Stehrer 2022) and positive effects of robot adoption on industry-level employment growth (Ghodsi et al. 2020). At the same time, there is consensus that automation and new technologies will reduce demand for low-skilled labour (Arntz, Gregory and Zierahn 2016; Acemoglu and Restrepo 2017, 2018; Graetz and Michaels 2018), which will have implications for wages that, although not fully clear from a theoretical standpoint, point towards a widening gap between the respective earnings of high- and low-skilled workers.

Consistent with the literature emphasising the differential impact on skills (Autor, Levy and Murnane 2003), our study uncovers a multifaceted influence of technology on wages. Our empirical findings reveal that patents as a measure of successful innovation activity (Van Hove 2010) positively correlates with wage increases, which supports the hypothesis that innovation drives economic rewards for workers – and especially those involved in the innovative activities themselves. However, by protecting the intellectual property rights of patents held by capital owners and, as a result, by increasing the sale of innovative goods with new capabilities, market share and, ultimately, profit and technological rents, the capital owners' share of added value exceeds the share of labour, which in turn leads to lower labour share income. Nonetheless, the impacts of robot intensity and ICT capital investment on labour income shares are intricate, echoing the findings of recent empirical studies (Graetz and Michaels 2018) and contributing to the discourse on job polarisation (Haiss, Mahlberg and Michlits 2021; Koch, Manuylov

and Smolka 2021). Building upon recent scholarly work (Autor and Salomons 2018), our research enriches the current understanding by accounting for the spill-over effects of technology through both domestic and international linkages within global value chains. Crucially, our methodology quantifies the effects of sector-specific technological advancements within a country on wages and labour income share while also capturing the impacts emanating from other sectors in the global economy, thereby delineating the aggregate net effects of global technological progress. We include technologies from domestic and international supplier and buyer sectors of a sector and analyse their impact on that specific sector. Moreover, total factor productivity (TFP), excluding the aforementioned technologies, will be incorporated into the analysis to account for other types of technologies and know-how.

In sum, our study offers a nuanced view of the interplay between technology and labour economics, contributing to a balanced understanding of how technological progress may lead to both opportunities and challenges in the labour market. As the dynamics of new technologies continue to evolve, our research provides a timely assessment of their implications for wage structures and the distribution of labour income.

In the following section, we provide a review of the literature. Section 3 discusses our data and introduces our empirical strategy. This is followed by a presentation of our econometric results in Section 4 and a concluding Section 5.

# 2. Literature review

Technological progress has been transforming labour markets throughout history, eliminating some jobs while creating new ones complementary to emerging technologies and simultaneously altering wages (Autor 2015). In recent decades, the adoption and improvement of ICT brought on by the Third Industrial Revolution, along with the proliferation of technologies introduced during the Fourth Industrial Revolution (e.g. robots, automation and, more recently, artificial intelligence), have been disrupting workplaces and raising widespread concerns about the future of jobs expressed through fears of 'risks of computerisation' (Arntz, Gregory and Zierahn 2016), 'risk of automation' (Arntz, Gregory and Zierahn 2019) and the potential for a 'jobless future' (Arnowitz and DiFazio 2010). Alongside concerns of technology-driven unemployment, labour's share of national income across many economies has been declining since the 1980s, with improvements in ICT (and the subsequent decrease in relative prices of investment goods) being identified as a significant factor affecting this trend (Karabarbounis and Neiman 2014; Eden and Gaggl 2018), although there is as yet no clear consensus on the magnitude of its importance (Autor et al. 2020). At the same time, demographic challenges characterised by shrinking working-age populations and ageing have started to threaten further economic growth across high- and upper-middle-income economies (Leitner and Stehrer 2019). Thus, these novel technologies provide an additional solution for filling labour market shortages besides increasing immigration numbers.

These developments have spurred a large stream of literature addressing the effects of automation, digitalisation and other novel technologies on the labour market. In the early stages of digitalisation, a significant body of work focused on exploring skills complementary to new technologies, with some also estimating effects on wages and inequality. Krueger's (1993) seminal paper highlighted the importance of computer skills for earning higher wages, while DiNardo and Pischke (1997) posited that higher-wage workers were more likely to use computers in their jobs. Early studies provided evidence of the complementarity between new technology (computers) and human capital, with computer adoption partly explaining the growing wage bill of higher-skilled workers (Autor, Katz and Krueger 1998). Subsequent research showed a shift in skill demand from basic computer skills to the ability to interpret and apply data (Autor 2015). Many studies focusing on the early effects of digitalisation observed changes in occupational structures and identified skilled-biased technological change (SBTC) (Katz and Murphy 1992), which suggested increasing demand and wages for high-skilled workers, followed by a rising wage gap and inequality due to increased returns to higher education (Baldwin and Cain 2000). Various studies incorporated different measures of technological change, including R&D intensity, high-tech capital usage and the recency of technology, all pointing to SBTC (e.g. Machin and Van Reenen 1998; Allen 2001).

Rapid improvements in computing power over time led to the automation of well-defined routine jobs, resulting in a decline in labour demand for middle-skilled, medium-wage workers (Arntz, Gregory and Zierahn 2019). Thus, while most evidence of SBTC pertains to the 1980s (Card and Di Nardo 2002), subsequent evidence indicated routine-biased technological change (RBTC) in the US and across developed European economies. RBTC is characterised by rising labour demand for highly skilled workers and for low-skilled workers employed in manual service jobs, while demand for both middle- and low-skilled workers in routine non-manual occupations falls (Autor, Levy and Murnane 2003; Goos and Manning 2007; Autor and Dorn 2013; Goos, Manning and Salomons 2014). The increasing demand for low-skill manual jobs, which are performed on site and in person, is due to income elasticity effects,

which generate demand for this low-technology sector even when it is not directly affected by technological change. Grigoli, Koczan and Topalova (2020) showed that workers displaced from routinised jobs were more likely to drop out of the labour force, underscoring the importance of active labour market policies, education and (re)training to mitigate these trends resulting from displacement, especially given the labour market shortages across the European countries they explored.

The anxiety surrounding the technological transformation of the workplace has been amplified by studies exploring the potential for computerisation and automation, indicating high levels of imminent disruption. Research providing high double-digit estimates of 'jobs at risk' employed the occupational approach pioneered by Frey and Osborne (2013), which estimated that 47% of US employment was threatened by computerisation while also emphasising the negative impact of this probability on the wages of the directly affected labour. These risks have proven to vary by country, from 36% in Finland (Pajarinen and Rouvinen 2014) to 59% in Germany (Brzeski and Burk 2015). Criticism of this approach centres on its undefined time frame and the crucial fact that automation typically affects tasks rather than entire occupations, leading to overestimations. Arntz, Gregory and Zierahn (2016) proposed a task-based approach to provide more realistic estimates of occupational changes, yielding significantly lower risk percentages: 9% in the US and an average of 21% across OECD countries, ranging from 12% in Austria to 6% in South Korea. Nedelkoska and Quintini (2018) found that, in 32 OECD countries, 14% of jobs are automatable, with the highest risk in Slovakia (33%) and the lowest in Norway (6%), with this variance being more attributable to differences in the organisation of job tasks than to the sectoral structure of these economies. These estimates only consider what is theoretically possible to automate, not whether it is economically feasible.

The proliferation and enhancement of ICT, initiated by the Third Industrial Revolution and intensified by the Fourth Industrial Revolution's adoption of robots, automation, artificial intelligence and other technologies, has heightened interest in the effects that adopting new technologies has on productivity, employment, wages and inequality, particularly since Schwab (2016) coined the term 'Fourth Industrial Revolution'. International economic institutions, such as the International Monetary Fund (2017), the World Bank (2016) and the World Trade Organisation (2017), have emphasised the proliferation of new technologies as a critical factor shaping labour markets, international trade and the global economic landscape. However, economic theory does not offer a clear-cut answer regarding the effects of technology adoption on labour demand, wages or the labour share of value added. Labour demand is influenced by two principal opposing effects resulting from technology adoption (Acemoglu and Restrepo 2020): (1) the displacement of workers by new technology, and (2) increased productivity due to price-productivity effects (as reduced production costs lead to industry expansion and increased labour demand) and scale-productivity effects (where cost reductions can augment total output and thereby enhance overall labour demand). Each technology has its particularities, with the level of labour's complementarity to new technologies, the elasticity of labour supply (which can affect wage outcomes), the demand elasticity of the product produced, and the income elasticity of demand being particularly crucial (Autor 2015). The automation of certain types of labour reduces its wage while also impacting the wages of others through ripple effects (Acemoglu and Restrepo 2018). Over the long term, new labour-intensive jobs will play a vital role in offsetting the effects of automation on employment, wages and inequality (Ibid.).

Labour displacement can occur in two forms: (1) employment displacement, which refers to a decrease in aggregate employment, and (2) labour share displacement, which refers to a shrinking labour share of value added (Autor and Salomons 2018). To estimate the overall effects, a rapidly growing body of literature has explored changes at the country, sectoral, regional and firm levels. While most productivity

effect estimates are positive, evidence of employment and wage effects is far from definitive, varying with the level of aggregation, methodology and scope of research. Particularly ambiguous is the evidence concerning the wage effects of new technologies, which remain relatively scarce. Using an industry-country panel approach, Graetz and Michaels (2018) found that investments in industrial robots across 17 countries from 1993 to 2007 were associated with higher wages and did not significantly reduce overall employment. Gregory, Salomons and Zierahn (2016) provided evidence for 27 European economies between 1999 and 2010, showing that routine-replacing technological change led to positive overall labour demand effects – rather than substitution effects – due to increased product demand and associated spill-overs, although they did not address wage effects. Research in various European countries has indicated diverse employment outcomes. For example, while Dauth et al. (2021) for Germany (1994-2014) and Dottori (2021) for Italy (1990-2016) did not find overall negative outcomes, Aghion, Antonin and Bunel (2019) observed negative effects in France for a similar period (1990-2014). Jestl (2022) examined the impact of industrial robots and ICT investment on employment in EU countries from 2001 to 2016 and discovered that only investment in software and databases had a negative impact on employment dynamics in both manufacturing and non-manufacturing, while IT investments had positive employment effects in local manufacturing industries. He noted negative employment effects in local manufacturing industries, positive effects in the local non-manufacturing sector, and relatively weak effects on total employment dynamics.

Acemoglu and Restrepo (2020; 2021) investigated the effects of robot adoption in the US and estimated that, from 1980 to 2016, each additional robot per 1,000 workers reduced the employment-to-population ratio by between 0.18 and 0.34 percentage points and wages by 0.25% to 0.5%. In the period from 1990 to 2007, the estimated effects were even stronger: a 0.37 percentage point decrease in the employment-to-population ratio and a 0.78% decrease in wage growth. Following the methodology of Acemoglu and Restrepo (2017), Chiacchio, Petropoulos and Pichler (2018) looked at six EU countries collectively accounting for 85.5% of the industrial robots in the EU and found that the robots reduced employment rate by between 0.16 and 0.20 percentage points in the period between 1995 and 2007. Borjas and Freeman (2019) highlighted negative effects of robots on employment that also led to a decrease in wages, estimating them to be more significant on employment and wages than those of additional immigration. In contrast, Dekle (2020) reported overall positive effects of robots on employment in Japan, which uses robots more intensively than the US and has a robot dataset from the 1970s, allowing for a longer time frame (1979-2012) to explore this relationship.

Several papers have utilised firm-level data to estimate the wage and labour share effects of novel technology adoption. Humlum (2019) found that industrial robots in Denmark increased average real wages by 0.8% while decreasing them for production workers by 6%. Koch, Manuylov and Smolka (2021), using firm-level data from Spain's manufacturing industry between 1990 and 2016, observed positive effects of robot adoption on employment but no significant average wage effects. Cheng et al. (2021) assessed the impact of automation on labour shares in China's manufacturing sector, noting a negative effect on the labour share of firms automating and suggesting that further decreases in robot prices could lead to significant income redistribution within these firms. Chiacchio, Petropoulos and Pichler (2018) posited that these effects might vary based on firm-level investment in human capital.

Critiques of the aforementioned studies often centre on the use of the Cobb-Douglas production function, whose high explanatory power may be attributable to the relationships between variables in the model (Sachs and Kotlikoff 2012; Felipe and McCombie 2020). Some studies have alternatively applied the constant elasticity of substitution (CES) production function (Stehrer, 2010). More pessimistic

forecasts, such as those by Sachs, Benzell and LaGarda (2015), using the overlapping generations model, suggest that if automation negatively impacts labour income – which is the sole savings source – it could impede economic growth through reduced savings and investment. Moreover, most research has focused on countries at the technological frontier, such as those in the EU or OECD, often overlooking the impacts on developing economies and the global production network.

Factors shaping labour supply and its elasticity – particularly ageing, education and migration trends (Docquier et al. 2019) – are also crucial in determining the wage effects of technological change. Globalisation – via import penetration, off-shoring and re-shoring driven by ICT adoption (Baldwin 2012) – and other determinants concurrently influence labour market outcomes. Pak and Schwellnus (2019) found that increased participation in global value chains was instrumental in reducing the labour share in 20 OECD countries between 1995 and 2011. They also highlighted the significance of government policies on employment and wages (DeCanio 2016). Using a difference-in-differences approach, they demonstrated the importance of pro-competition product market reforms and active labour market policies in enhancing the labour share at the expense of producers' rents while also indicating that labour market reforms that bolster employees' bargaining power could be counterproductive in the long term, as they may nudge firms towards capital-labour substitution. Additionally, Ciminelli, Duval and Furceri (2022) found deregulation to have detrimental effects on the labour share in a sample of 26 advanced economies from 1970 to 2013. Conversely, Stockhammer (2017) attributed labour share displacement primarily to financialisation in a sample of 43 developing and 28 advanced economies from 1970 to 2007. A recent study by Autor et al. (2020), using US micro-level panel data from 1982 to 2012, linked 'superstar firms' with a declining labour share of income, particularly in industries undergoing intense technological change.

Recent studies have begun to explore the global effects of new technologies, providing evidence along the value chains (Ghodsi et al. 2020; Autor and Salomons 2018). Ghodsi et al. (2020) documented the impact of robot adoption on employment and value added across 41 countries included in the World Input-Output Database (WIOD) for the 2000-2014 period, noting a positive effect on employment growth at the sectoral level globally. Autor and Salomons (2018) observed that labour share losses in industries affected by automation are not offset elsewhere, although the negative employment effects in the directly affected sectors are counterbalanced by an indirect rise in employment in consumer industries and an increase in aggregate demand. These studies form the basis for this research, which aims to further assess the impact on wages along the global value chains.

Vivarelli (2022) and Dosi et al. (2021) highlighted the significance of sectoral shifts in the workforce resulting from robot adoption, from robot-utilising 'downstream sectors' to robot-producing 'upstream sectors', with implications for investment in 'downstream sectors'. Consequently, while labour displacement by new technologies does occur, the aggregate demand for labour does not necessarily decrease due to industry output effects, cross-industry input-output effects, inter-industry shifts and final demand effects (Autor and Salomons 2018). Contrasting with much of the research focused on developed economies, Faber (2020) provided insights from an off-shoring country, Mexico (1990-2015), demonstrating that robot installation in developed economies could alter global value chains through re-shoring activities, potentially reducing employment and exports in off-shoring countries. These findings underscore the importance of analysing effects through global value chains and estimating the global impact of novel technologies on employment, wages and the labour share.

# 3. Data and methodological approach

This section outlines the primary databases used in this study and presents the methodology employed for the analysis.

## 3.1. DATA SOURCES

Several databases have been collated for this analysis. Industry-country level data on gross fixed capital formation (GFCF), capital stocks, ICT GFCF, value added, employment, labour compensation and gross output have been sourced from the Structural Analysis Database (STAN) database of the Organisation for Economic Co-operation and Development (OECD). Data on industrial robots have been compiled from the International Federation of Robotics (IFR), while patent data have been gathered from the Amadeus database provided by Bureau van Dijk, including only patents granted by offices and using the year of publication as the year of the patent. These patents are linked to their owning firms and respective sectors, with additional firm and sector information coming from the Orbis database of Bureau van Dijk. TFP is estimated using the method of Ackerberg, Caves and Frazer (2015), which assesses real value added against the number of employed persons, with investment as a proxy and capital stock, robot stocks and granted patents as state variables. TFP represents the residual value added not accounted for by these variables but by other factors, such as managerial skills and other types of technologies. The OECD's Trade in Value Added (TiVA) database is used to examine the significance of domestic and international backward and forward linkages. Figure D1 in Appendix D presents the development of aggregated variables in the study sample over years. Table C2 in Appendix C present the aggregated variables across countries in the study sample averaged over the period.

## 3.2. METHODOLOGY

In this study, we estimate the level of wages and the share of wages in value added as a function of technologies. The estimation equation is as follows:

$$W_{ict} = exp^{\{\alpha_0+\beta_1 S_{ict}+\beta_2 ICT_{ict}+\beta_3 pat_{ict}+\beta_4 pat_{ict}^{env}+\beta_5 TFP_{ict}+\beta_2 K_{ict}+\delta_{ci}+\delta_{ci}+\varepsilon_{ict}\}} \quad (1)$$

where $W_{ict}$ is either the labour share in value added or the average wage of employed persons in a given sector $i$ and country $c$ at time $t$; $S_{ict}$ is the set of variables on intensity of robots, which is calculated as stock of industrial robots installed relative to the persons employed in the given country-sector-year combination; $ICT_{ict}$ denotes the share of ICT investment in total capital GFCF in a country-sector-year combination; $pat_{ict}$ is the set of variables on the number of granted patents in all technology classes that are published in the given country-sector-year combination; $TFP_{ict}$ is the total factor productivity (TFP) estimated using the Ackerberg, Caves and Frazer (2015) methodology while controlling for the aforementioned types of technologies in the given country-sector-year combination; and $K_{ict}$ is the capital stock that is used following the standard literature on the labour demand function (e.g. Hijzen and Swaim 2010). All variables are in constant 2015 USD. $\delta_{ci}$, $\delta_{ct}$ are, respectively, country-

industry and country-year fixed effects that respectively control for technological shocks within an industry in a country and business cycles in a country; and $\varepsilon_{ict}$ is the standard errors.

As mentioned above, the dependent variable is either the average wage or the labour, which are estimated in separate estimations to give their related interpretations. Average wages are calculated as the labour compensation (in constant 2015 USD) divided by the number of persons employed. The labour income share is calculated as labour compensation relative to total value added in nominal terms. We test the impact of new technologies on wages and labour income shares both in levels and in growth rates or first differences. When the dependent variable is in levels or first difference, all other variables are also included in levels or first differences. The benchmark estimations are run using the ordinary least squares (OLS) method with robust standard errors clustering for country-industry and country-year fixed effects to control for within-country-industry and country-year autocorrelation of the error term. Moreover, as a robustness check of the level estimations, the Poisson pseudo-maximum-likelihood (PPML) estimator developed by Correia, Guimarães and Zylkin (2019) is applied, which is also robust against heteroscedasticity. As capital stocks are not reported for many industry-country combinations, a robustness check is run excluding capital, ICT investment and TFP, while labour productivity in terms of value added is included instead and robot stocks are included instead of robot intensity.

We augment these technology variables by incorporating interactions with global value chain indicators. Specifically, we aim to measure the technologies in the international and domestic suppliers and buyers of an industry. Utilising technical coefficients within the global value chains, four distinct measures are constructed. The variable $X$ measured in the domestic suppliers of an industry, calculated using the domestic backward ($DBW$) linkages, and the variable $X$ measured for the domestic buyers of an industry, using its domestic forward ($DFW$) linkages, are computed as follows:

$$lnX_{c,i,t}^{DBW} = \sum_{j(j\neq i)}^{J} l_{(cj,ci),t} \times lnX_{c,j,t}$$
$$lnX_{c,i,t}^{DFW} = \sum_{j(j\neq i)}^{J} g_{(ci,cj),t} \times lnX_{c,j,t} \quad (2)$$

The subscript $j \neq i$ in the coefficient of the Leontief $l_{(cj,ci),t}$ and Ghosh $g_{(ci,cj),t}$ coefficient indicates that the linkage term excludes within-industry linkages for a given industry $i$, where $J$ denotes the total number of industries.

The variables of international suppliers and buyers using international linkages are defined analogously, only that in this case both the intra-industry and cross-country linkages within the GVCs are included, as these do not constitute within-industry linkages in the same country. Assigning the index $f$ to the foreign countries with which the international backward ($IBW$) and international forward ($IFW$) linkages are established and, with the total number of countries $F$, they are defined as follows:

$$lnX_{c,i,t}^{IBW} = \sum_{j=1}^{J} \sum_{f(f \neq c)}^{F} l_{(fj,ci),t} \times lnX_{f,j,t}$$
$$lnX_{c,i,t}^{IFW} = \sum_{j=1}^{J} \sum_{f(f \neq c)}^{F} g_{(ci,fj),t} \times lnX_{f,j,t} \quad (3)$$

The typical element of the Leontief inverse, $l_{(fj,ci),t}$, indicates the purchases of industry $i$ in country $c$ from foreign country $f$'s industry $j$ at time $t$. Note that here the purchases of industry $i$ in country $c$ from all foreign supplier industry $i$'s are included.[1] Likewise, the typical element of the Ghosh inverse, $g_{(ci,fj),t}$, indicates the sales of industry $i$ in country $c$ to foreign country $f$'s industry $j$ at time $t$.

[1] The reason is that, say, a purchase by the Chinese steel industry from the Indian steel industry is an inter-industry transaction.

# 4. Estimation results

In this section, we first report the results of the estimations starting with the relation between wage levels and the technology variables, followed by the results concerning the labour income shares. Then, in the next subsection, we report results when considering growth of average wages and changes in labour income shares.

## 4.1. RESULTS FOR LEVELS

We present two sets of results: first, we consider the impact of the aforementioned proxies for new technologies (controlling for TFP and capital stock or capital intensity), and then we also account for GVC linkages (reporting the joint effect, again controlling for TFP and capital stock or capital intensity). Detailed results and robustness checks using lagged variables are included in Appendix A. Table 1 reports the findings related to wage levels. While the upper panel displays results without GVC linkages, the lower panel considers GVC linkages as joint effects. The first two columns, (1) and (2), show results for the sample where all variables are available; columns (3) and (4) present findings for a larger country sample but exclude capital variables not available for all countries at the industry level. Since capital stocks are not reported for many industry-country combinations, a robustness check is run excluding capital. We focus our discussion on the first set of results using PPML (i.e. column 2).

In Panel A (excluding GVC linkages), we observe that the number of patents, as a proxy for innovation activities, has a significantly positive relationship with wage levels: a 1% increase in patents correlates with a wage increase of about 0.045%. However, we do not find any significant effect of robot stock or ICT investments on wages. Both TFP levels and capital stocks are positively associated with wages. For the larger sample (columns 3 and 4), the positive correlation between patents and wages persists, albeit with a smaller coefficient. Furthermore, we detect a small but significant positive effect of robot intensity on wages. These results are robust in specifications using lagged variables (see Table A.5).

When accounting for the effects of technologies through domestic and international suppliers and buyers via GVC linkages, we observe a stronger positive relationship between patents and wages, with a coefficient of 0.078. Additionally, robot intensity is significantly negatively correlated with wage levels; a 1% increase in robot intensity corresponds to a reduction in wages by about 0.3%. The share of ICT investment, however, does not exhibit a significant impact. As expected, we find significant positive relationships with respect to TFP and capital-labour ratios, in line with the results above. Detailed examination (see Table A.1) suggests that the direct effects are qualitatively similar to the baseline regression, though the magnitudes do vary in some cases. The role of international backward linkages is notably significant in explaining the higher coefficient for patents. Country-industries with strong backward linkages to entities with robust patent activities can command higher wages. Regarding robot stock, all four GVC linkages have a significant negative effect on wage levels. For ICT investments, international linkages neutralise each other, leading to an insignificant effect on wages.

**Table 1 / Estimation results on technology adoption and average wage levels, 1996-2017**

| **Panel A: Baseline results** | **OLS** | **PPML** | **OLS** | **PPML** |
|---|---|---|---|---|
| **Dependent variable: average wage** | **(1)** | **(2)** | **(3)** | **(4)** |
| Log of number of granted patents | 0.045*** | 0.045*** | 0.0082*** | 0.0088*** |
| | (0.0023) | (0.0029) | (0.0018) | (0.0026) |
| Log of intensity of stock robots in number of | -0.000044 | 0.00084 | 0.018*** | 0.012** |
| Persons engaged in total employment | (0.0033) | (0.0037) | (0.0026) | (0.0049) |
| Log of share of ICT investment in GFCF | 0.0026 | 0.023 | | |
| | (0.019) | (0.025) | | |
| TFP (columns 1 and 2) or labour productivity (columns 3 and 4) | 1.28*** | 1.45*** | 0.70*** | 0.74*** |
| | (0.028) | (0.044) | (0.015) | (0.047) |
| Capital stock | 0.33*** | 0.33*** | | |
| | (0.015) | (0.018) | | |
| Constant | 5.88*** | 6.49*** | 6.44*** | 7.28*** |
| | (0.11) | (0.15) | (0.058) | (0.21) |
| Observations | 14732 | 14732 | 22926 | 22926 |
| R-squared | 0.993 | | 0.993 | |
| Adjusted R-squared | 0.992 | | 0.993 | |
| Pseudo R-squared | | 0.980 | | 0.975 |
| AIC | -14917.1 | 7956952.6 | -18467.9 | 16322671.7 |
| BIC | -14871.5 | 7956998.2 | -18435.7 | 16322703.9 |

| **Panel B: Including GVC linkages (joint effects)** | **OLS** | **PPML** | **OLS** | **PPML** |
|---|---|---|---|---|
| **Dependent variable: average wage** | **(1)** | **(2)** | **(3)** | **(4)** |
| Log number of granted patents | .072*** | .078*** | .035** | .052*** |
| | (0) | (0) | (.01) | (.001) |
| Log robot intensity | -.283*** | -.339*** | .003 | -.131*** |
| | (0) | (0) | (.947) | (.005) |
| Log of share of ICT investment | -.114 | -1.365 | | |
| | (.914) | (.235) | | |
| TFP (columns 1 and 2); labour productivity (columns 3 and 4) | 2.097*** | 2.133*** | .912*** | .864*** |
| | (0) | (0) | (0) | (0) |
| Capital-labour ratio | .311*** | .318*** | | |
| | (0) | (0) | | |
| No. of obs. | 14732 | 14732 | 22926 | 22926 |
| Adjusted R-squared | .993 | .982 | .994 | .978 |

Note: ***, **, * means significance at 1, 5 and 10% level; standard errors in brackets.

These findings are broadly supported when considering the larger sample (see columns 3 and 4 of Table A.1) as well as when using lagged variables (Table A.2). Table A.7 in the Appendix replicates Model 1, and Table A.8 replicates Model 2, as presented in Table 1. In these tables, the technological variables are included in separate estimations. The R-square and adjusted R-square values of these estimations, excluding explanatory variables, indicate that a significant portion of the wage variations is explained by the fixed effects and the constant of the model. Additionally, the impacts of most technological variables remain robust and are consistent with those in the full model presented in Table 1.

**Table 2 / Estimation results on technology adoption and labour income shares, 1996-2017**

| **Panel A: Baseline results** | **OLS** | **PPML** | **OLS** | **PPML** |
|---|---|---|---|---|
| **Dependent variable: labour income share** | **(1)** | **(2)** | **(3)** | **(4)** |
| Log of number of granted patents | -0.0053*** | -0.014*** | -0.0019*** | -0.0055** |
| | (0.00083) | (0.0022) | (0.00070) | (0.0026) |
| Log of intensity of stock robots in number of | 0.0049*** | 0.021*** | -0.00048 | 0.0028 |
| persons engaged in total employment | (0.0016) | (0.0050) | (0.00088) | (0.0024) |
| Log of share of ICT investment in GFCF | 0.0042 | 0.029 | | |
| | (0.0095) | (0.025) | | |
| TFP (columns 1 and 2) or labour productivity (columns 3 and 4) | -0.14*** | -0.44*** | -0.032*** | -0.12*** |
| | (0.016) | (0.056) | (0.0025) | (0.019) |
| Capital stock-labour ratio | -0.045*** | -0.19*** | | |
| | (0.0074) | (0.031) | | |
| Constant | 0.95*** | 1.07*** | 0.63*** | -0.095 |
| | (0.058) | (0.23) | (0.0092) | (0.070) |
| Observations | 16941 | 16941 | 29274 | 29274 |
| R-squared | 0.895 | | 0.847 | |
| Adjusted R-squared | 0.885 | | 0.835 | |
| Pseudo R-squared | | 0.060 | | 0.064 |
| AIC | -47270.9 | 24713.4 | -67768.3 | 43533.7 |
| BIC | -47224.5 | 24759.9 | -67735.1 | 43566.8 |

| **Panel B: Including GVC linkages (joint effects)** | **OLS** | **PPML** | **OLS** | **PPML** |
|---|---|---|---|---|
| **Dependent variable: labour income share** | **(1)** | **(2)** | **(3)** | **(4)** |
| Log of number of granted patents | .005 | .002 | .017*** | .041* |
| | (.516) | (.922) | (.001) | (.053) |
| Log of intensity of stock robots in number of | -.06*** | -.255*** | -.098*** | -.399*** |
| persons engaged in total employment | (.006) | (0) | (0) | (0) |
| Log of share of ICT investment | -.167 | -2.464* | | |
| | (.797) | (.079) | | |
| TFP (columns 1 and 2); labour productivity (columns 3 and 4) | .382*** | 1.235*** | .081*** | .254*** |
| | (0) | (0) | (0) | (0) |
| Capital stock | -.01* | -.046** | | |
| | (.063) | (.015) | | |
| No. of obs. | 17325 | 17325 | 29274 | 29274 |
| Adjusted R-squared | .893 | .06 | .85 | .066 |

Note: ***, **, * means significance at 1, 5 and 10% level; standard errors in brackets.

Regarding labour income shares (Table 2), we note a slight negative effect of the number of patents and a positive effect of robot intensity in the baseline specifications (excluding linkages) when considering TFP and capital stocks (columns 1 and 2). The ICT investment share does not significantly affect labour income shares. In the larger sample (columns 3 and 4), only the negative relationship between patent activities and labour income shares is substantiated. TFP and the capital-labour ratio are negatively associated with labour income shares. These findings are corroborated when employing lagged variables (Table A.6). Table A.9 in the Appendix replicates Model 1, and Table A.10 replicates Model 2, as presented in Table 2. In these tables, the technological variables are included in separate estimations. The R-square and adjusted R-square values of these estimations, excluding explanatory variables, indicate that a significant portion of the labour income share variations is explained by the fixed effects and the constant of the model. Additionally, the impacts of most technological variables remain robust and are consistent with those in the full model presented in Table 2.

When considering the effects of technologies through GVC linkages (Panel B of Table 2), the number of patents does not have a significant impact in these specifications. As with the wage results, this is primarily due to the positive effect of international backward linkages (detailed in Table A.3). Robot intensity is also negatively correlated with labour income shares, influenced by the strong negative effects of both domestic and international forward linkages. The ICT investment share is once again significantly negatively related to labour income shares, this time due to a substantial negative impact from international backward linkages. TFP positively correlates with labour income shares when factoring in linkage effects (mostly due to domestic and international backward linkages). Similar to the baseline, the capital-labour ratio negatively impacts labour income shares. These results are consistently confirmed with lagged explanatory variables (see Table A.4).

## 4.2. RESULTS FOR CHANGES OVER TIME

Table 3 presents the OLS estimation results using yearly changes in all variables. Growth in the number of patents positively affects wage levels but negatively impacts labour income shares within the smaller sample (which allows controlling for capital and TFP). In the larger country sample, increased patent activities correlate with stronger wage growth, although the coefficient is considerably smaller than in the other sample. We also observe a positive relationship between the growth of robot intensity and ICT capital with labour income shares, but not with wage growth. TFP and capital growth relate positively to wage growth but negatively to labour income shares.

When considering the effects of technologies through GVC linkages (refer to Panel B of Table 3), there are virtually no significant relationships between technology variables and either wage growth or changes in labour income shares. A detailed examination of the results (Table B.1) reveals that the effects of GVC linkages are insignificant in most instances (with the exception of international backward linkages for robot intensity), suggesting that the direct effects are the predominant (and significant) factors.

The preceding comprehensive set of estimations has yielded multifaceted insights into the impact of diverse novel technologies on wages and labour income shares. This aligns with the theoretical framework proposed by Autor (2015), which underscores the technology-specific nuances shaping the employment and wage outcomes. Results indicating a positive effect of patents, robots and TFP on wages contribute to the broader dialogue on the ‘productivity bandwagon’, while the negative effects of some technological indicators on labour income share hint at ‘so-so automation’ (Johnson and Acemoglu 2023). Our conclusions are aligned with recent research pointing to a generally limited impact of technologies on wages and labour income shares.

**Table 3 / OLS estimation results on technology adoption and growth in wages and changes in labour share, 1996-2017**

**Panel A: Baseline results**

| Dependent variable: | Growth of wage level (1) | Change in labour income shares (2) | Growth of wage level (3) | Change in labour income shares (4) |
|---|---|---|---|---|
| Difference of log of number of granted patents | 0.018*** | -0.019*** | 0.0017 | 0.0016** |
| | (0.0028) | (0.0024) | (0.0013) | (0.00066) |
| Difference of log of intensity of stock robots in number of persons engaged in total employment | -0.0049 | 0.0069*** | 0.012* | 0.0036 |
| | (0.0070) | (0.0025) | (0.0074) | (0.0027) |
| Difference of log of share of ICT investment in GFCF | 0.0083 | 0.011* | | |
| | (0.0080) | (0.0068) | | |
| Difference in TFP (columns 1 and 2) or labour productivity (columns 3 and 4) | 0.46*** | -0.64*** | 0.47*** | -0.26*** |
| | (0.076) | (0.076) | (0.031) | (0.026) |
| Difference in capital | 0.28*** | -0.081*** | | |
| | (0.035) | (0.024) | | |
| Constant | 0.0088*** | 0.0038*** | 0.0099*** | 0.0041*** |
| | (0.0011) | (0.00068) | (0.0010) | (0.00064) |
| Observations | 14048 | 16156 | 22252 | 27897 |
| R-squared | 0.264 | 0.499 | 0.365 | 0.231 |
| Adjusted R-squared | 0.194 | 0.450 | 0.313 | 0.168 |
| AIC | -27564.6 | -56721.7 | -36486.0 | -65620.8 |
| BIC | -27519.3 | -56675.6 | -36454.0 | -65587.9 |

**Panel B: Including GVC linkages (joint effects)**

| Dependent variable: | Growth of wage level (1) | Change in labour income shares (2) | Growth of wage level (3) | Change in labour income shares (4) |
|---|---|---|---|---|
| Difference of log of number of granted patents | .052 | .012 | .081 | .063* |
| | (.436) | (.675) | (.217) | (.095) |
| Difference of log of intensity of stock robots in number of persons engaged in total employment | .123 | -.003 | .162 | .158** |
| | (.517) | (.965) | (.255) | (.023) |
| Difference of log of share of ICT investment in GFCF | -.589 | -.398 | | |
| | (.676) | (.633) | | |
| Difference in TFP (col. 1 and 2) or labour productivity (col. 3 and 4) | -1.13* | -1.3*** | .069 | -1.069*** |
| | (.058) | (0) | (.785) | (0) |
| Difference in capital or capital intensity | .281*** | -.134*** | | |
| | (0) | (.001) | | |
| No. of obs. | 14048 | 16540 | 22252 | 27897 |
| Adjusted R-squared | .204 | .451 | .099 | .129 |

Note: ***, **, * means significance at 1, 5 and 10% level; standard errors in brackets.

# 5. Summary and concluding remarks

This paper advances the literature on the effects of new technologies on labour markets by examining their impact on wage growth and labour income shares, an area less traversed compared to employment studies. Our study delves deeper into the repercussions of individual technologies, exceeding the single-country framework of the groundwork studies in this field (Acemoglu and Restrepo 2021; Acemoglu and Restrepo 2020; Borjas and Freeman 2019) while also assessing the broader landscape by providing empirical evidence for multi-country-sample and GVC effects, following Autor and Salomon's (2018) approach. Thus, besides showing the direct implications of diverse novel technologies in a certain sector, it also sheds light on their effects along the GVCs, as suggested by Jurkat, Klump and Schneider (2023).

While our empirical outcomes are not entirely definitive, they do suggest that technological innovation, as proxied by patents, significantly and positively correlates with wage levels, although it does have a minor negative effect on labour income shares, indicating an incomplete transfer of technology rents to labour. This perspective further provides valuable insights to the literature exploring determinants of declining labour share (e.g., Ciminelli, Duval and Furceri, 2022; Stockhammer 2017), also providing important insights for policymakers. Notably, robot intensity reveals a substantial positive link with labour income shares, in contrast to ICT capital, which demonstrates no significant correlation. These trends hold when analysing year-on-year changes.

Our investigation highlights that patent growth bolsters wage increases but inversely impacts labour income shares. The interplay with GVC linkages amplifies the positive correlation between patents and wages. Specifically, the joint effects of patents held by the international and domestic suppliers and buyers of a sector have a positive impact on that sector's wages. The influence of robot intensity on wages and labour income share is positive, but it is turned negative by GVC linkages, suggesting a complex interplay between technology and income distribution. In fact, there are strong negative effects on wages originating in domestic and international buyers of a sector that is automating. This suggests important sectoral changes stemming from the introduction of robots, including the shifts in employment from robot-utilising to robot-producing sectors (Vivarelli 2022; Dosi et al. 2021). This shift might be influenced by reshoring activities (as shown for Mexico by Faber, 2020) which further impact wages and labour income share along the chain. The effects of ICT investment remain largely stable within the GVC context. Echoing recent studies with minimal or slightly positive findings on new technologies' impact on employment, our results similarly show only modest effects on wages and labour income shares. These dynamics highlight the need for further comprehensive exploration of GVC linkages, particularly in highly integrated sectors, given the potential sectoral shifts accompanying diverse types of technological advancements. Moreover, these results underscore the role of considering technological changes within GVCs in policymaking, given its implications for economic and social upgrading paths across countries. Our research paves the way for future studies to delve deeper into the implications of the ongoing technological changes on wages and redistribution of income along GVCs.

These outcomes, which indicate a positive effect of patents, robots and TFP on wages, contribute to the broader dialogue on the ‘productivity bandwagon’, while the negative effects of some technological indicators on labour income share hint at the ‘so-so automation’, as theorised by Johnson and Acemoglu (2023). It is noteworthy that the direct effect of patenting in a sector negatively affects its labour share income, as capital owners of intellectual property rights accrue profits and rents. Meanwhile, the overall global effects of patenting on labour share income, which also include the positive impacts through patenting by international suppliers of that sector, become statistically insignificant. This evidence shows that the global value chains play an important role in diversifying the innovation rents of patenting across sectors and countries that compensate for the losses of labour income shares due to protection of property rights of patents by their owners in each sector.

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# Appendix

## APPENDIX A – DETAILED RESULTS AND ROBUSTNESS CHECKS FOR LEVELS

### Table A.1 / Wage levels

| | OLS | PPML | OLS | PPML |
|---|---|---|---|---|
| Log of number of granted patents | 0.045*** | 0.043*** | 0.0077*** | 0.0068*** |
| | (0.0021) | (0.0028) | (0.0018) | (0.0026) |
| D-BW Log of number of granted patents | -0.015 | -0.0027 | -0.013 | 0.0010 |
| | (0.013) | (0.016) | (0.010) | (0.016) |
| D-FW Log of number of granted patents | -0.015** | -0.033*** | -0.012** | -0.017** |
| | (0.0069) | (0.0077) | (0.0057) | (0.0086) |
| I-BW Log of number of granted patents | 0.066*** | 0.059*** | 0.062*** | 0.065*** |
| | (0.0060) | (0.0052) | (0.0047) | (0.0052) |
| I-FW Log of number of granted patents | -0.0097** | 0.012** | -0.010** | -0.0034 |
| | (0.0049) | (0.0055) | (0.0041) | (0.0058) |
| TFP or labour productivity in VA | 1.32*** | 1.54*** | 0.72*** | 0.76*** |
| | (0.030) | (0.045) | (0.015) | (0.049) |
| bD TFP or labour productivity in VA | 0.51*** | 0.50*** | 0.17*** | 0.17*** |
| | (0.065) | (0.067) | (0.012) | (0.016) |
| fD TFP or labour productivity in VA | 0.039 | 0.10** | -0.00049 | -0.0048 |
| | (0.036) | (0.040) | (0.0064) | (0.0092) |
| bI TFP or labour productivity in VA | 0.51*** | 0.43*** | 0.024** | -0.012 |
| | (0.11) | (0.071) | (0.011) | (0.014) |
| fI TFP or labour productivity in VA | -0.28*** | -0.44*** | -0.0051 | -0.046*** |
| | (0.060) | (0.076) | (0.0075) | (0.012) |
| Log of intensity of stock robots in number of persons engaged in total employment | -0.0012 | -0.0030 | 0.0026 | 0.0079 |
| | (0.0033) | (0.0040) | (0.0028) | (0.0061) |
| D-BW Log of intensity of stock robots in number of persons engaged in total employment | -0.10** | -0.098*** | -0.053 | -0.011 |
| | (0.043) | (0.034) | (0.043) | (0.033) |
| D-FW Log of intensity of stock robots in number of persons engaged in total employment | -0.020 | -0.069*** | 0.033** | -0.035*** |
| | (0.015) | (0.014) | (0.013) | (0.013) |
| I-BW Log of intensity of stock robots in number of persons engaged in total employment | -0.14*** | -0.084** | 0.065*** | -0.062 |
| | (0.037) | (0.034) | (0.025) | (0.052) |
| I-FW Log of intensity of stock robots in number of persons engaged in total employment | -0.025 | -0.084*** | -0.044** | -0.031 |
| | (0.024) | (0.025) | (0.020) | (0.024) |
| Log of share of ICT investment in GFCF | 0.0075 | 0.020 | | |
| | (0.020) | (0.027) | | |
| D-BW Log of share of ICT investment in GFCF | 0.65 | 0.56 | | |
| | (0.70) | (0.73) | | |
| D-FW Log of share of ICT investment in GFCF | 0.43** | 0.31 | | |
| | (0.20) | (0.27) | | |
| I-BW Log of share of ICT investment in GFCF | -2.74*** | -3.65*** | | |
| | (0.72) | (0.56) | | |
| I-FW Log of share of ICT investment in GFCF | 1.54*** | 1.39** | | |
| | (0.52) | (0.60) | | |
| Capital stock | 0.31*** | 0.32*** | | |
| | (0.016) | (0.018) | | |
| Constant | 5.43*** | 6.07*** | 5.86*** | 6.76*** |
| | (0.12) | (0.16) | (0.061) | (0.24) |
| Observations | 14732 | 14732 | 22926 | 22926 |
| R-squared | 0.993 | | 0.994 | |
| Adjusted R-squared | 0.993 | | 0.994 | |
| Pseudo R-squared | | 0.982 | | 0.978 |
| AIC | -16682.7 | 6927663.4 | -21124.4 | 14734694.3 |
| BIC | -16515.6 | 6927830.5 | -20995.7 | 14734822.9 |

Note: Standard errors in brackets; ***, **, * means significance at 1, 5 and 10% level.

## Table A.2 / Wage levels; regressions using lagged variables

| | OLS | PPML | OLS | PPML |
|---|---|---|---|---|
| Log of number of granted patents | 0.044*** | 0.044*** | 0.015*** | 0.017*** |
| | (0.0023) | (0.0033) | (0.0022) | (0.0036) |
| D-BW Log of number of granted patents | -0.017 | -0.0092 | -0.025* | -0.025 |
| | (0.013) | (0.016) | (0.013) | (0.022) |
| D-FW Log of number of granted patents | -0.018** | -0.035*** | 0.0069 | 0.031* |
| | (0.0081) | (0.0095) | (0.0086) | (0.016) |
| I-BW Log of number of granted patents | 0.061*** | 0.047*** | 0.073*** | 0.041*** |
| | (0.0071) | (0.0064) | (0.0063) | (0.0079) |
| I-FW Log of number of granted patents | -0.0069 | 0.015** | -0.0021 | 0.010 |
| | (0.0054) | (0.0069) | (0.0050) | (0.0084) |
| TFP or labour productivity in VA | 1.20*** | 1.34*** | 0.41*** | 0.49*** |
| | (0.034) | (0.049) | (0.017) | (0.051) |
| bD TFP or labour productivity in VA | 0.43*** | 0.45*** | 0.098*** | 0.11*** |
| | (0.066) | (0.069) | (0.014) | (0.028) |
| fD TFP or labour productivity in VA | 0.066* | 0.14*** | -0.017* | -0.037** |
| | (0.039) | (0.043) | (0.0091) | (0.019) |
| bI TFP or labour productivity in VA | 0.31*** | 0.33*** | -0.032** | -0.0022 |
| | (0.11) | (0.084) | (0.015) | (0.022) |
| fI TFP or labour productivity in VA | -0.20*** | -0.46*** | -0.013 | -0.084*** |
| | (0.069) | (0.095) | (0.0099) | (0.016) |
| Log of intensity of stock robots in number of | 0.00044 | 0.0019 | 0.017*** | 0.032*** |
| persons engaged in total employment | (0.0037) | (0.0046) | (0.0039) | (0.0073) |
| D-BW Log of intensity of stock robots in number of | -0.11** | -0.11*** | 0.017 | 0.14** |
| persons engaged in total employment | (0.043) | (0.037) | (0.040) | (0.055) |
| D-FW Log of intensity of stock robots in number of | -0.0036 | -0.060*** | 0.065*** | -0.040 |
| persons engaged in total employment | (0.018) | (0.018) | (0.019) | (0.024) |
| I-BW Log of intensity of stock robots in number of | -0.082** | -0.065 | 0.19*** | -0.22** |
| persons engaged in total employment | (0.040) | (0.042) | (0.035) | (0.090) |
| I-FW Log of intensity of stock robots in number of | -0.029 | -0.051 | -0.046* | 0.062 |
| persons engaged in total employment | (0.028) | (0.033) | (0.025) | (0.039) |
| Log of share of ICT investment in GFCF | 0.0027 | 0.017 | | |
| | (0.023) | (0.028) | | |
| D-BW Log of share of ICT investment in GFCF | 0.72 | 0.41 | | |
| | (0.67) | (0.70) | | |
| D-FW Log of share of ICT investment in GFCF | 0.34 | 0.26 | | |
| | (0.21) | (0.28) | | |
| I-BW Log of share of ICT investment in GFCF | -1.99*** | -3.12*** | | |
| | (0.74) | (0.65) | | |
| I-FW Log of share of ICT investment in GFCF | 1.20** | 1.56** | | |
| | (0.58) | (0.73) | | |
| Capital stock | 0.28*** | 0.28*** | | |
| | (0.017) | (0.020) | | |
| Constant | 5.83*** | 6.69*** | 7.28*** | 8.22*** |
| | (0.12) | (0.17) | (0.079) | (0.26) |
| Observations | 14092 | 14092 | 22012 | 22012 |
| R-squared | 0.992 | | 0.990 | |
| Adjusted R-squared | 0.992 | | 0.989 | |
| Pseudo R-squared | | 0.978 | | 0.961 |
| AIC | -13801.1 | 8256051.7 | -9566.7 | 24966770.4 |
| BIC | -13634.9 | 8256217.8 | -9438.7 | 24966898.4 |

Note: Standard errors in brackets; ***, **, * means significance at 1, 5 and 10% level.

## Table A.3 / Labour income shares

| | OLS | PPML | OLS | PPML |
|---|---|---|---|---|
| Log of number of granted patents | -0.0049*** | -0.011*** | -0.0015** | -0.0025 |
| | (0.00076) | (0.0021) | (0.00067) | (0.0020) |
| D-BW Log of number of granted patents | 0.0051 | 0.0019 | 0.010** | 0.015 |
| | (0.0070) | (0.018) | (0.0039) | (0.013) |
| D-FW Log of number of granted patents | -0.0065*** | -0.025*** | -0.0034* | -0.018** |
| | (0.0023) | (0.0064) | (0.0020) | (0.0077) |
| I-BW Log of number of granted patents | 0.015*** | 0.034*** | 0.016*** | 0.051*** |
| | (0.0019) | (0.0059) | (0.0018) | (0.010) |
| I-FW Log of number of granted patents | -0.0033* | 0.0024 | -0.0040** | -0.0041 |
| | (0.0019) | (0.0053) | (0.0018) | (0.0055) |
| TFP or labour productivity in VA | -0.076*** | -0.25*** | -0.029*** | -0.11*** |
| | (0.011) | (0.048) | (0.0024) | (0.017) |
| bD TFP or labour productivity in VA | 0.24*** | 0.65*** | 0.073*** | 0.20*** |
| | (0.036) | (0.10) | (0.0055) | (0.025) |
| fD TFP or labour productivity in VA | 0.034* | 0.20*** | 0.0012 | 0.029** |
| | (0.018) | (0.050) | (0.0031) | (0.014) |
| bI TFP or labour productivity in VA | 0.19*** | 0.68** | 0.036*** | 0.16*** |
| | (0.050) | (0.27) | (0.0062) | (0.044) |
| fI TFP or labour productivity in VA | -0.00099 | -0.039 | 0.000046 | -0.024 |
| | (0.018) | (0.059) | (0.0035) | (0.021) |
| Log of intensity of stock robots in number of | -0.0020 | -0.00085 | 0.000085 | 0.0080* |
| persons engaged in total employment | (0.0013) | (0.0038) | (0.0011) | (0.0048) |
| D-BW Log of intensity of stock robots in number of | -0.044*** | -0.16*** | -0.064*** | -0.17*** |
| persons engaged in total employment | (0.013) | (0.040) | (0.0092) | (0.030) |
| D-FW Log of intensity of stock robots in number of | -0.013** | -0.045*** | -0.0045 | -0.039** |
| persons engaged in total employment | (0.0056) | (0.014) | (0.0038) | (0.017) |
| I-BW Log of intensity of stock robots in number of | 0.029** | 0.029 | -0.0054 | -0.18** |
| persons engaged in total employment | (0.014) | (0.051) | (0.012) | (0.089) |
| I-FW Log of intensity of stock robots in number of | -0.030*** | -0.079*** | -0.024*** | -0.015 |
| persons engaged in total employment | (0.0073) | (0.019) | (0.0091) | (0.032) |
| Log of share of ICT investment in GFCF | 0.0077 | 0.038 | | |
| | (0.011) | (0.027) | | |
| D-BW Log of share of ICT investment in GFCF | 0.065 | -0.87 | | |
| | (0.55) | (1.18) | | |
| D-FW Log of share of ICT investment in GFCF | 0.071 | -0.17 | | |
| | (0.14) | (0.31) | | |
| I-BW Log of share of ICT investment in GFCF | -0.39 | -2.45* | | |
| | (0.29) | (1.46) | | |
| I-FW Log of share of ICT investment in GFCF | 0.078 | 0.99 | | |
| | (0.17) | (0.62) | | |
| Capital stock-labour ratio | -0.010* | -0.046** | | |
| | (0.0056) | (0.019) | | |
| Constant | 0.49*** | -0.32 | 0.39*** | -0.85*** |
| | (0.069) | (0.24) | (0.011) | (0.045) |
| Observations | 17325 | 17325 | 29274 | 29274 |
| R-squared | 0.902 | | 0.862 | |
| Adjusted R-squared | 0.893 | | 0.850 | |
| Pseudo R-squared | | 0.060 | | 0.066 |
| AIC | -49438.4 | 25345.3 | -70696.7 | 43479.7 |
| BIC | -49267.7 | 25516.0 | -70564.2 | 43612.2 |

Note: Standard errors in brackets; ***, **, * means significance at 1, 5 and 10% level.

## Table A.4 / Labour income shares; regressions using lagged variables

| | OLS | PPML | OLS | PPML |
|---|---|---|---|---|
| Log of number of granted patents | -0.0033*** | -0.0048* | -0.00092 | -0.0041 |
| | (0.00078) | (0.0026) | (0.00071) | (0.0031) |
| D-BW Log of number of granted patents | 0.00087 | -0.014 | 0.010*** | 0.018 |
| | (0.0064) | (0.026) | (0.0035) | (0.013) |
| D-FW Log of number of granted patents | -0.0078*** | -0.024*** | -0.0029 | -0.023** |
| | (0.0027) | (0.0085) | (0.0023) | (0.0089) |
| I-BW Log of number of granted patents | 0.0065*** | -0.00100 | 0.0068*** | 0.0033 |
| | (0.0024) | (0.011) | (0.0020) | (0.0084) |
| I-FW Log of number of granted patents | -0.0049*** | -0.0047 | -0.0055*** | -0.018** |
| | (0.0018) | (0.0056) | (0.0017) | (0.0078) |
| TFP or labour productivity in VA | -0.035*** | -0.089** | -0.017*** | -0.066*** |
| | (0.0099) | (0.045) | (0.0020) | (0.016) |
| bD TFP or labour productivity in VA | 0.12*** | 0.17** | 0.042*** | 0.078*** |
| | (0.025) | (0.083) | (0.0044) | (0.016) |
| fD TFP or labour productivity in VA | 0.010 | 0.084* | -0.0011 | 0.035** |
| | (0.014) | (0.046) | (0.0034) | (0.018) |
| bI TFP or labour productivity in VA | 0.15*** | 0.51** | 0.024*** | 0.13*** |
| | (0.048) | (0.20) | (0.0064) | (0.039) |
| fI TFP or labour productivity in VA | 0.033* | 0.14* | -0.00011 | -0.0047 |
| | (0.019) | (0.078) | (0.0036) | (0.013) |
| Log of intensity of stock robots in number of | -0.0031** | -0.0017 | -0.00081 | 0.0026 |
| persons engaged in total employment | (0.0013) | (0.0044) | (0.0012) | (0.0042) |
| D-BW Log of intensity of stock robots in number of | -0.044*** | -0.12** | -0.058*** | -0.11*** |
| persons engaged in total employment | (0.014) | (0.050) | (0.010) | (0.034) |
| D-FW Log of intensity of stock robots in number of | -0.0057 | -0.021* | -0.00035 | -0.020 |
| persons engaged in total employment | (0.0047) | (0.012) | (0.0041) | (0.014) |
| I-BW Log of intensity of stock robots in number of | 0.024* | 0.015 | -0.0017 | -0.13* |
| persons engaged in total employment | (0.014) | (0.046) | (0.015) | (0.067) |
| I-FW Log of intensity of stock robots in number of | -0.0058 | -0.015 | 0.0083 | 0.12* |
| persons engaged in total employment | (0.0084) | (0.024) | (0.013) | (0.065) |
| Log of share of ICT investment in GFCF | 0.0014 | 0.028 | | |
| | (0.010) | (0.035) | | |
| D-BW Log of share of ICT investment in GFCF | 0.62* | 2.35* | | |
| | (0.33) | (1.29) | | |
| D-FW Log of share of ICT investment in GFCF | 0.29*** | 0.55** | | |
| | (0.086) | (0.28) | | |
| I-BW Log of share of ICT investment in GFCF | -0.18 | 0.87 | | |
| | (0.35) | (2.03) | | |
| I-FW Log of share of ICT investment in GFCF | -0.23 | -0.88 | | |
| | (0.18) | (0.82) | | |
| Capital stock-labour ratio | -0.0037 | -0.039 | | |
| | (0.0057) | (0.025) | | |
| Constant | 0.44*** | -0.44* | 0.45*** | -0.61*** |
| | (0.062) | (0.25) | (0.010) | (0.057) |
| Observations | 16551 | 16551 | 28095 | 28095 |
| R-squared | 0.893 | | 0.851 | |
| Adjusted R-squared | 0.882 | | 0.839 | |
| Pseudo R-squared | | 0.059 | | 0.065 |
| AIC | -45697.4 | 24233.5 | -65909.3 | 41772.2 |
| BIC | -45527.7 | 24403.2 | -65777.4 | 41904.1 |

Note: Standard errors in brackets; ***, **, * means significance at 1, 5 and 10% level.

## Table A.5 / Wage levels without linkages and using lagged variables

| | OLS | PPML | OLS | PPML |
|---|---|---|---|---|
| Log of number of granted patents | 0.044*** | 0.047*** | 0.016*** | 0.017*** |
| | (0.0024) | (0.0033) | (0.0023) | (0.0036) |
| TFP or labour productivity in VA | 1.16*** | 1.27*** | 0.42*** | 0.48*** |
| | (0.032) | (0.048) | (0.017) | (0.049) |
| Log of intensity of stock robots in number of | 0.0039 | 0.0054 | 0.044*** | 0.028*** |
| persons engaged in total employment | (0.0037) | (0.0042) | (0.0034) | (0.0053) |
| Log of share of ICT investment in GFCF | -0.0031 | 0.019 | | |
| | (0.021) | (0.026) | | |
| Capital stock | 0.30*** | 0.29*** | | |
| | (0.016) | (0.020) | | |
| Constant | 6.21*** | 7.01*** | 7.59*** | 8.42*** |
| | (0.11) | (0.17) | (0.068) | (0.22) |
| Observations | 14092 | 14092 | 22012 | 22012 |
| R-squared | 0.992 | | 0.990 | |
| Adjusted R-squared | 0.991 | | 0.989 | |
| Pseudo R-squared | | 0.976 | | 0.959 |
| AIC | -12787.5 | 8949094.5 | -8394.2 | 25709367.7 |
| BIC | -12742.2 | 8949139.8 | -8362.2 | 25709399.7 |

Note: Standard errors in brackets; ***, **, * means significance at 1, 5 and 10% level.

## Table A.6 / Labour income shares without linkages and using lagged variables

| | OLS | PPML | OLS | PPML |
|---|---|---|---|---|
| Log of number of granted patents | -0.0033*** | -0.0061** | -0.0014* | -0.0059* |
| | (0.00082) | (0.0025) | (0.00072) | (0.0033) |
| TFP or labour productivity in VA | -0.069*** | -0.16*** | -0.019*** | -0.069*** |
| | (0.015) | (0.060) | (0.0020) | (0.016) |
| Log of intensity of stock robots in number of | 0.0021 | 0.012** | -0.00080 | 0.0012 |
| persons engaged in total employment | (0.0015) | (0.0049) | (0.00089) | (0.0024) |
| Log of share of ICT investment in GFCF | -0.0054 | 0.016 | | |
| | (0.0094) | (0.039) | | |
| Capital stock-labour ratio | -0.042*** | -0.18*** | | |
| | (0.0076) | (0.040) | | |
| Constant | 0.84*** | 0.65*** | 0.58*** | -0.26*** |
| | (0.053) | (0.23) | (0.0075) | (0.064) |
| Observations | 16166 | 16166 | 28095 | 28095 |
| R-squared | 0.890 | | 0.846 | |
| Adjusted R-squared | 0.879 | | 0.833 | |
| Pseudo R-squared | | 0.059 | | 0.064 |
| AIC | -44227.5 | 23603.3 | -64955.6 | 41767.1 |
| BIC | -44181.4 | 23649.5 | -64922.6 | 41800.1 |

Note: Standard errors in brackets; ***, **, * means significance at 1, 5 and 10% level.

## Table A.7 / Wage levels without linkages and using OLS and including variables separately

| | M1 | M2 | M3 | M4 | M5 | M6 | M7 |
|---|---|---|---|---|---|---|---|
| Log of number of granted patents | | | 0.018*** | | | | 0.045*** |
| | | | (0.0035) | | | | (0.0023) |
| Log of intensity of stock robots in number of | | | | 0.063*** | | | -0.000044 |
| persons engaged in total employment | | | | (0.0050) | | | (0.0033) |
| Log of share of ICT investment in GFCF | | | | | 0.0028 | | 0.0026 |
| | | | | | (0.029) | | (0.019) |
| TFP or labour productivity in VA | | | | | | 1.26*** | 1.28*** |
| | | | | | | (0.027) | (0.028) |
| Capital stock | | 0.38*** | 0.38*** | 0.36*** | 0.38*** | 0.33*** | 0.33*** |
| | | (0.018) | (0.018) | (0.018) | (0.018) | (0.015) | (0.015) |
| Constant | 9.56*** | 7.44*** | 7.39*** | 7.52*** | 7.44*** | 6.04*** | 5.88*** |
| | (0.0020) | (0.10) | (0.10) | (0.100) | (0.100) | (0.10) | (0.11) |
| Observations | 14732 | 14732 | 14732 | 14732 | 14732 | 14732 | 14732 |
| R-squared | 0.982 | 0.984 | 0.984 | 0.984 | 0.984 | 0.992 | 0.993 |
| Adjusted R-squared | 0.980 | 0.982 | 0.982 | 0.982 | 0.982 | 0.992 | 0.992 |
| AIC | -1854.5 | -3089.1 | -3122.7 | -3307.6 | -3087.1 | -14412.3 | -14917.1 |
| BIC | -1846.9 | -3073.9 | -3099.9 | -3284.8 | -3064.4 | -14389.5 | -14871.5 |

Note: Standard errors in brackets; ***, **, * means significance at 1, 5 and 10% level.

## Table A.8 / Wage levels without linkages and using PPML and including variables separately

| | M1 | M2 | M3 | M4 | M5 | M6 | M7 |
|---|---|---|---|---|---|---|---|
| Log of number of granted patents | | | 0.010** | | | | 0.045*** |
| | | | (0.0044) | | | | (0.0029) |
| Log of intensity of stock robots in number | | | | 0.072*** | | | 0.00084 |
| of persons engaged in total employment | | | | (0.0049) | | | (0.0037) |
| Log of share of ICT investment in GFCF | | | | | 0.018 | | 0.023 |
| | | | | | (0.028) | | (0.025) |
| TFP or labour productivity in VA | | | | | | 1.41*** | 1.45*** |
| | | | | | | (0.041) | (0.044) |
| Capital stock | | 0.33*** | 0.33*** | 0.32*** | 0.34*** | 0.33*** | 0.33*** |
| | | (0.022) | (0.022) | (0.021) | (0.022) | (0.018) | (0.018) |
| Constant | 10.7*** | 8.76*** | 8.72*** | 8.83*** | 8.75*** | 6.74*** | 6.49*** |
| | (0.0025) | (0.13) | (0.13) | (0.13) | (0.13) | (0.14) | (0.15) |
| Observations | 14732 | 14732 | 14732 | 14732 | 14732 | 14732 | 14732 |
| Pseudo R-squared | 0.951 | 0.954 | 0.955 | 0.956 | 0.954 | 0.979 | 0.980 |
| AIC | 18885856.9 | 17677462.8 | 17662231.6 | 17231567.4 | 17676388.6 | 8242869.4 | 7956952.6 |
| BIC | 18885864.5 | 17677478.0 | 17662254.4 | 17231590.2 | 17676411.4 | 8242892.2 | 7956998.2 |

Note: Standard errors in brackets; ***, **, * means significance at 1, 5 and 10% level.

**Table A.9 / Labour income shares without linkages and using OLS and including variables separately**

| | M1 | M2 | M3 | M4 | M5 | M6 | M7 |
|---|---|---|---|---|---|---|---|
| Log of number of granted patents | | | -0.0023*** | | | | -0.0053*** |
| | | | (0.00082) | | | | (0.00083) |
| Log of intensity of stock robots in number of persons engaged in total employment | | | | -0.0017 | | | 0.0049*** |
| | | | | (0.0012) | | | (0.0016) |
| Log of share of ICT investment in GFCF | | | | | 0.0043 | | 0.0042 |
| | | | | | (0.010) | | (0.0095) |
| TFP or labour productivity in VA | | | | | | -0.13*** | -0.14*** |
| | | | | | | (0.016) | (0.016) |
| Capital stock | | -0.048*** | -0.048*** | -0.048*** | -0.048*** | -0.044*** | -0.045*** |
| | | (0.0080) | (0.0081) | (0.0082) | (0.0080) | (0.0072) | (0.0074) |
| Constant | 0.51*** | 0.77*** | 0.78*** | 0.77*** | 0.77*** | 0.93*** | 0.95*** |
| | (0.00051) | (0.045) | (0.044) | (0.046) | (0.045) | (0.056) | (0.058) |
| Observations | 16941 | 16941 | 16941 | 16941 | 16941 | 16941 | 16941 |
| R-squared | 0.884 | 0.886 | 0.886 | 0.886 | 0.886 | 0.895 | 0.895 |
| Adjusted R-squared | 0.873 | 0.876 | 0.876 | 0.876 | 0.876 | 0.885 | 0.885 |
| AIC | -45545.2 | -45861.3 | -45867.8 | -45861.3 | -45859.9 | -47210.8 | -47270.9 |
| BIC | -45537.5 | -45845.8 | -45844.6 | -45838.1 | -45836.7 | -47187.6 | -47224.5 |

Note: Standard errors in brackets; ***, **, * means significance at 1, 5 and 10% level

**Table A.10 / Labour income shares without linkages and using PPML and including variables separately**

| | M1 | M2 | M3 | M4 | M5 | M6 | M7 |
|---|---|---|---|---|---|---|---|
| Log of number of granted patents | | | -0.0027 | | | | -0.014*** |
| | | | (0.0022) | | | | (0.0022) |
| Log of intensity of stock robots in number of persons engaged in total employment | | | | 0.0034 | | | 0.021*** |
| | | | | (0.0042) | | | (0.0050) |
| Log of share of ICT investment in GFCF | | | | | 0.035 | | 0.029 |
| | | | | | (0.032) | | (0.025) |
| TFP or labour productivity in VA | | | | | | -0.42*** | -0.44*** |
| | | | | | | (0.055) | (0.056) |
| Capital stock | | -0.21*** | -0.21*** | -0.21*** | -0.21*** | -0.19*** | -0.19*** |
| | | (0.049) | (0.050) | (0.050) | (0.049) | (0.031) | (0.031) |
| Constant | -0.54*** | 0.59** | 0.60** | 0.59** | 0.58** | 0.99*** | 1.07*** |
| | (0.0021) | (0.26) | (0.26) | (0.27) | (0.26) | (0.22) | (0.23) |
| Observations | 16941 | 16941 | 16941 | 16941 | 16941 | 16941 | 16941 |
| Pseudo R-squared | 0.058 | 0.059 | 0.059 | 0.059 | 0.059 | 0.060 | 0.060 |
| AIC | 24745.1 | 24735.8 | 24737.8 | 24737.8 | 24737.7 | 24708.7 | 24713.4 |
| BIC | 24752.8 | 24751.3 | 24761.0 | 24761.0 | 24760.9 | 24732.0 | 24759.9 |

Note: Standard errors in brackets; ***, **, * means significance at 1, 5 and 10% level

# APPENDIX B – DETAILED RESULTS AND ROBUSTNESS CHECKS FOR CHANGES

## Table B.1 / Detailed results

| | Average wages | Labour income shares | Average wages | Labour income shares |
|---|---|---|---|---|
| Difference in log of number of granted patents | 0.018*** | -0.019*** | 0.0016 | 0.0015** |
| | (0.0027) | (0.0023) | (0.0013) | (0.00066) |
| D-BW Difference in log of number of granted patents | 0.0053 | -0.0052 | -0.012 | -0.0070 |
| | (0.019) | (0.0086) | (0.015) | (0.0093) |
| D-FW Difference in log of number of granted patents | -0.012 | -0.0022 | 0.00020 | 0.0012 |
| | (0.0097) | (0.0037) | (0.0064) | (0.0029) |
| I-BW Difference in log of number of granted patents | -0.025 | 0.018 | -0.0031 | 0.060* |
| | (0.075) | (0.035) | (0.064) | (0.033) |
| I-FW Difference in log of number of granted patents | 0.064 | 0.020 | 0.091** | 0.0083 |
| | (0.058) | (0.026) | (0.045) | (0.031) |
| Growth in TFP or labour productivity in VA | 0.48*** | -0.64*** | 0.47*** | -0.26*** |
| | (0.074) | (0.073) | (0.032) | (0.027) |
| Growth in bD TFP or labour productivity in VA | 0.18 | -0.065 | -0.013 | -0.090 |
| | (0.29) | (0.19) | (0.11) | (0.072) |
| Growth in fD TFP or labour productivity in VA | -0.40** | -0.14** | -0.079 | -0.046 |
| | (0.19) | (0.060) | (0.068) | (0.028) |
| Growth in bI TFP or labour productivity in VA | 0.47 | 0.19 | 0.30 | 0.22 |
| | (0.69) | (0.32) | (0.26) | (0.14) |
| Growth in fI TFP or labour productivity in VA | -1.85*** | -0.66*** | -0.84*** | -0.56*** |
| | (0.49) | (0.18) | (0.17) | (0.15) |
| Difference in log of intensity of stock robots in number of persons engaged | -0.0089 | 0.0021 | 0.0068 | 0.00051 |
| | (0.0071) | (0.0026) | (0.0076) | (0.0030) |
| D-BW Difference in log of intensity of stock robots in number of persons engaged | -0.086 | -0.057* | -0.071 | -0.057 |
| | (0.11) | (0.034) | (0.11) | (0.035) |
| D-FW Difference in log of intensity of stock robots in number of persons engaged | -0.013 | -0.026 | 0.00065 | -0.019 |
| | (0.060) | (0.017) | (0.048) | (0.015) |
| I-BW Difference in log of intensity of stock robots in number of persons engaged | 0.34* | 0.11** | 0.48*** | 0.14** |
| | (0.18) | (0.051) | (0.12) | (0.055) |
| I-FW Difference in log of intensity of stock robots in number of persons engaged | -0.11 | -0.033 | -0.11 | 0.042 |
| | (0.12) | (0.037) | (0.099) | (0.085) |
| Difference in log of share of ICT investment in GFCF | 0.0012 | 0.0036 | | |
| | (0.0084) | (0.0076) | | |
| D-BW Difference in log of share of ICT investment in GFCF | -0.47 | -0.55 | | |
| | (0.31) | (0.37) | | |
| D-FW Difference in log of share of ICT investment in GFCF | -0.31 | -0.31 | | |
| | (0.26) | (0.30) | | |
| I-BW Difference in log of share of ICT investment in GFCF | -0.89 | -0.22 | | |
| | (1.25) | (0.58) | | |
| I-FW Difference in log of share of ICT investment in GFCF | 1.08 | 0.67 | | |
| | (1.21) | (0.51) | | |
| Capital growth | 0.28*** | -0.13*** | | |
| | (0.033) | (0.042) | | |
| Constant | 0.0089*** | 0.0054*** | 0.0082*** | 0.0034*** |
| | (0.0027) | (0.0013) | (0.0026) | (0.0013) |
| Observations | 14048 | 16540 | 22252 | 27897 |
| R-squared | 0.275 | 0.499 | 0.370 | 0.236 |
| Adjusted R-squared | 0.204 | 0.451 | 0.318 | 0.172 |
| AIC | -27734.8 | -57975.7 | -36631.9 | -65763.3 |
| BIC | -27568.7 | -57806.0 | -36503.7 | -65631.6 |

Note: Standard errors in brackets; ***, **, * means significance at 1, 5 and 10% level.

## Table B.2 / Detailed results, 1 lag

| | Average wages | Labour income shares | Average wages | Labour income shares |
|---|---|---|---|---|
| Difference in log of number of granted patents | 0.00051 | 0.0070*** | -0.0015 | -0.000068 |
| | (0.0018) | (0.0025) | (0.0015) | (0.00068) |
| D-BW Difference in log of number of granted patents | 0.025 | 0.00037 | 0.0095 | -0.0019 |
| | (0.018) | (0.0085) | (0.015) | (0.0093) |
| D-FW Difference in log of number of granted patents | 0.028** | 0.0035 | 0.010 | 0.0033 |
| | (0.012) | (0.0050) | (0.0080) | (0.0030) |
| I-BW Difference in log of number of granted patents | 0.11 | 0.0027 | 0.14** | -0.073 |
| | (0.095) | (0.042) | (0.067) | (0.045) |
| I-FW Difference in log of number of granted patents | -0.044 | -0.0049 | -0.040 | -0.00020 |
| | (0.070) | (0.032) | (0.049) | (0.032) |
| Growth in TFP or labour productivity in VA | 0.041 | 0.25*** | -0.016 | 0.097*** |
| | (0.030) | (0.078) | (0.016) | (0.026) |
| Growth in bD TFP or labour productivity in VA | 0.29 | 0.31* | 0.18* | -0.10 |
| | (0.26) | (0.19) | (0.11) | (0.10) |
| Growth in fD TFP or labour productivity in VA | 0.24 | -0.0014 | 0.052 | 0.0082 |
| | (0.18) | (0.094) | (0.070) | (0.033) |
| Growth in bI TFP or labour productivity in VA | -0.061 | 0.0072 | 0.12 | -0.051 |
| | (0.52) | (0.30) | (0.27) | (0.12) |
| Growth in fI TFP or labour productivity in VA | 0.22 | 0.072 | -0.057 | 0.059 |
| | (0.44) | (0.17) | (0.17) | (0.11) |
| Difference in log of intensity of stock robots in number of persons engaged | 0.0033 | -0.0053* | -0.0014 | -0.0015 |
| | (0.0092) | (0.0030) | (0.0081) | (0.0026) |
| D-BW Difference in log of intensity of stock robots in number of persons engaged | 0.085 | -0.018 | 0.046 | -0.012 |
| | (0.088) | (0.028) | (0.080) | (0.023) |
| D-FW Difference in log of intensity of stock robots in number of persons engaged | -0.016 | 0.0014 | 0.016 | 0.0062 |
| | (0.055) | (0.015) | (0.045) | (0.013) |
| I-BW Difference in log of intensity of stock robots in number of persons engaged | -0.21 | -0.100 | -0.20 | -0.13** |
| | (0.28) | (0.061) | (0.18) | (0.060) |
| I-FW Difference in log of intensity of stock robots in number of persons engaged | 0.074 | 0.047 | 0.14 | 0.18*** |
| | (0.13) | (0.050) | (0.12) | (0.064) |
| Difference in log of share of ICT investment in GFCF | 0.012 | 0.021 | | |
| | (0.0076) | (0.019) | | |
| D-BW Difference in log of share of ICT investment in GFCF | 0.22 | 1.82 | | |
| | (0.16) | (1.22) | | |
| D-FW Difference in log of share of ICT investment in GFCF | 0.086 | 0.88* | | |
| | (0.12) | (0.51) | | |
| I-BW Difference in log of share of ICT investment in GFCF | 0.11 | -1.34** | | |
| | (1.23) | (0.67) | | |
| I-FW Difference in log of share of ICT investment in GFCF | -2.59*** | -0.27 | | |
| | (0.96) | (0.41) | | |
| Capital growth | -0.026 | 0.077 | | |
| | (0.022) | (0.048) | | |
| Constant | 0.011*** | -0.0036** | 0.014*** | 0.00073 |
| | (0.0029) | (0.0015) | (0.0028) | (0.0016) |
| Observations | 13408 | 16237 | 21854 | 27897 |
| R-squared | 0.159 | 0.194 | 0.133 | 0.103 |
| Adjusted R-squared | 0.075 | 0.115 | 0.061 | 0.029 |
| AIC | -24389.0 | -49016.2 | -28842.1 | -61303.1 |
| BIC | -24223.9 | -48846.9 | -28714.2 | -61171.4 |

Note: Standard errors in brackets; ***, **, * means significance at 1, 5 and 10% level.

**Table B.3 / No linkages using lagged variables**

| | Average wages | Labour income shares | Average wages | Labour income shares |
|---|---|---|---|---|
| Difference in log of number of granted patents | 0.00013 | 0.0076*** | -0.0017 | -0.000092 |
| | (0.0018) | (0.0029) | (0.0015) | (0.00067) |
| Growth in TFP or labour productivity in VA | 0.042 | 0.26*** | -0.017 | 0.098*** |
| | (0.031) | (0.091) | (0.016) | (0.026) |
| Difference in log of intensity of stock robots in number of persons engaged | 0.00050 | -0.0068** | -0.0032 | -0.0010 |
| | (0.0082) | (0.0030) | (0.0074) | (0.0024) |
| Difference in log of share of ICT investment in GFCF | 0.0092 | -0.0049 | | |
| | (0.0073) | (0.0071) | | |
| Capital growth | -0.026 | 0.0027 | | |
| | (0.022) | (0.029) | | |
| Constant | 0.015*** | -0.0013 | 0.020*** | -0.0017*** |
| | (0.00099) | (0.00082) | (0.00095) | (0.00064) |
| Observations | 13408 | 15381 | 21854 | 27897 |
| R-squared | 0.155 | 0.142 | 0.132 | 0.102 |
| Adjusted R-squared | 0.072 | 0.055 | 0.060 | 0.028 |
| AIC | -24360.2 | -45283.7 | -28833.9 | -61293.3 |
| BIC | -24315.2 | -45237.9 | -28801.9 | -61260.3 |

Note: Standard errors in brackets; ***, **, * means significance at 1, 5 and 10% level.

# APPENDIX C

## Table C.1 / Industry classification of sample (based on NACE Rev. 2)

| | |
|---|---|
| Agriculture | A |
| Mining, utilities and construction | B |
| Food products, beverages and tobacco | C10-C12 |
| Textiles, textile products, leather and footwear | C13-C15 |
| Wood and products of wood and cork | C16 |
| Paper products and printing | C17-C18 |
| Manufacture of coke and refined petroleum and chemical products | C19-C20 |
| Manufacture of basic pharmaceutical products and pharmaceutical preparations | C21 |
| Manufacture of rubber and plastic products | C22 |
| Manufacture of other non-metallic mineral products | C23 |
| Manufacture of basic metals | C24 |
| Manufacture of fabricated metal products, except machinery and equipment | C25 |
| Manufacture of computer, electronic and optical products | C26 |
| Manufacture of electrical equipment | C27 |
| Manufacture of machinery and equipment n.e.c. | C28 |
| Manufacture of motor vehicles, trailers and semi-trailers | C29 |
| Manufacture of other transport equipment | C30 |
| Manufacturing n.e.c.; repair and installation of machinery and equipment | C31-C33 |
| Electricity, gas, steam and air conditioning supply, water and sewerage | D-E |
| Construction | F |
| Wholesale and retail trade; repair of motor vehicles | G |
| Land transport and transport via pipelines | H49 |
| Water transport | H50 |
| Air transport | H51 |
| Warehousing and support activities for transportation | H52 |
| Postal and courier activities | H53 |
| Accommodation and food service activities | I |
| Publishing, audiovisual and broadcasting activities | J58J60 |
| Telecommunications | J61 |
| IT and other information services | J62-J63 |
| Financial and insurance activities | K |
| Real estate activities | L |
| Professional, scientific and technical activities; administrative and support services | MtN&P |
| Public administration and defence; compulsory social security | O |
| Human health and social work activities | Q |
| Arts, entertainment and recreation | R |
| Other service activities | S |
| Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use | T |

**Table C.2 / Aggregated variables at the country level averaged over the period**

| Country | ISO | Labour productivity in value added, constant 2015 USD 10th | TFP in value added estimated via ACF | Intensity of stock robots in number of persons employed | Share of ICT in capital | Number of granted patents, 100th | Share of wages in value added | Average labour cost for each employed person |
|---|---|---|---|---|---|---|---|---|
| Australia | AU | 7.58 | 7.38 | 0.15 | 0.01 | 0.041 | 0.56 | 59,178 |
| Austria | AT | 11.31 | 6.45 | 1.74 | 0.01 | 0.058 | 0.54 | 54,976 |
| Belgium | BE | 14.42 | 7.66 | 1.63 | 0.01 | 0.047 | 0.60 | 64,389 |
| Canada | CA | 11.39 | 9.95 | 0.67 | 0.02 | 0.093 | 0.61 | 54,778 |
| Chile | CL | 2.13 | 5.73 | | | 0.001 | 0.44 | 14,187 |
| Colombia | CO | 1.07 | | 0.01 | | 0.001 | 0.40 | 6,685 |
| Costa Rica | CR | 2.45 | | | | | 0.46 | 16,116 |
| Czechia | CZ | 4.16 | 3.93 | 2.15 | 0.24 | 0.016 | 0.50 | 18,303 |
| Germany | DE | 10.71 | 6.36 | 3.73 | | 0.788 | 0.61 | 52,572 |
| Denmark | DK | 15.35 | 7.49 | 1.69 | 0.05 | 0.049 | 0.60 | 68,152 |
| Spain | ES | 9.45 | 5.21 | 1.47 | | 0.054 | 0.54 | 40,273 |
| Estonia | EE | 4.20 | 4.86 | 0.13 | 0.01 | 0.001 | 0.60 | 21,179 |
| Finland | FI | 12.89 | 7.86 | 1.50 | 0.01 | 0.066 | 0.57 | 53,340 |
| France | FR | 12.36 | 7.70 | 1.06 | 0.01 | 0.280 | 0.62 | 61,083 |
| United Kingdom | UK | 14.20 | 8.79 | 0.54 | 0.01 | 0.168 | 0.60 | 67,011 |
| Greece | EL | 10.34 | 6.97 | 0.09 | | 0.001 | 0.49 | 24,617 |
| Hungary | HU | 4.34 | 3.04 | 1.09 | | 0.002 | 0.53 | 15,152 |
| Ireland | IE | 12.89 | 8.81 | 0.19 | | 0.021 | 0.48 | 49,571 |
| Iceland | IS | 12.53 | 8.36 | | | 0.002 | 0.70 | 62,743 |
| Israel | IL | 5.32 | 10.17 | 0.22 | 0.02 | 0.042 | 0.54 | 56,917 |
| Italy | IT | 11.43 | 6.29 | 2.04 | 0.01 | 0.098 | 0.53 | 41,180 |
| Japan | JP | 5.83 | 5.34 | 5.59 | 0.79 | 2.670 | 0.53 | 44,536 |
| South Korea | KR | 5.74 | 4.41 | 7.69 | | 1.012 | 0.48 | 32,597 |
| Lithuania | LT | 5.15 | 4.28 | 0.07 | 0.01 | 0.001 | 0.50 | 16,480 |
| Luxembourg | LU | 11.26 | 12.42 | | 0.01 | 0.016 | 0.63 | 66,403 |
| Latvia | LV | 3.46 | | 0.02 | | 0.001 | 0.60 | 17,479 |
| Mexico | MX | 5.35 | 6.60 | 0.46 | | 0.005 | 0.33 | 11,262 |
| Netherlands | NL | 15.85 | 8.34 | 0.90 | 0.01 | 0.157 | 0.53 | 59,896 |
| Norway | NO | 17.53 | 9.13 | 0.33 | 0.04 | 0.022 | 0.63 | 82,011 |
| New Zealand | NZ | 3.77 | 6.87 | 0.16 | | 0.006 | 0.52 | 43,328 |
| Poland | PL | 3.16 | 5.58 | 0.46 | | 0.018 | 0.43 | 12,868 |
| Portugal | PT | 6.86 | 5.34 | 0.72 | 0.01 | 0.003 | 0.54 | 26,270 |
| Slovakia | SK | 4.72 | 4.06 | 2.24 | 0.00 | 0.003 | 0.47 | 18,273 |
| Slovenia | SI | 6.00 | 4.65 | 2.17 | 0.00 | 0.004 | 0.59 | 28,473 |
| Sweden | SE | 13.49 | 7.39 | 2.31 | 0.12 | 0.118 | 0.51 | 58,071 |
| Turkey | TR | 2.03 | | 0.38 | | 0.005 | 0.41 | 17,552 |
| United States | US | 18.80 | 7.79 | 1.34 | 0.01 | 2.736 | 0.56 | 77,292 |

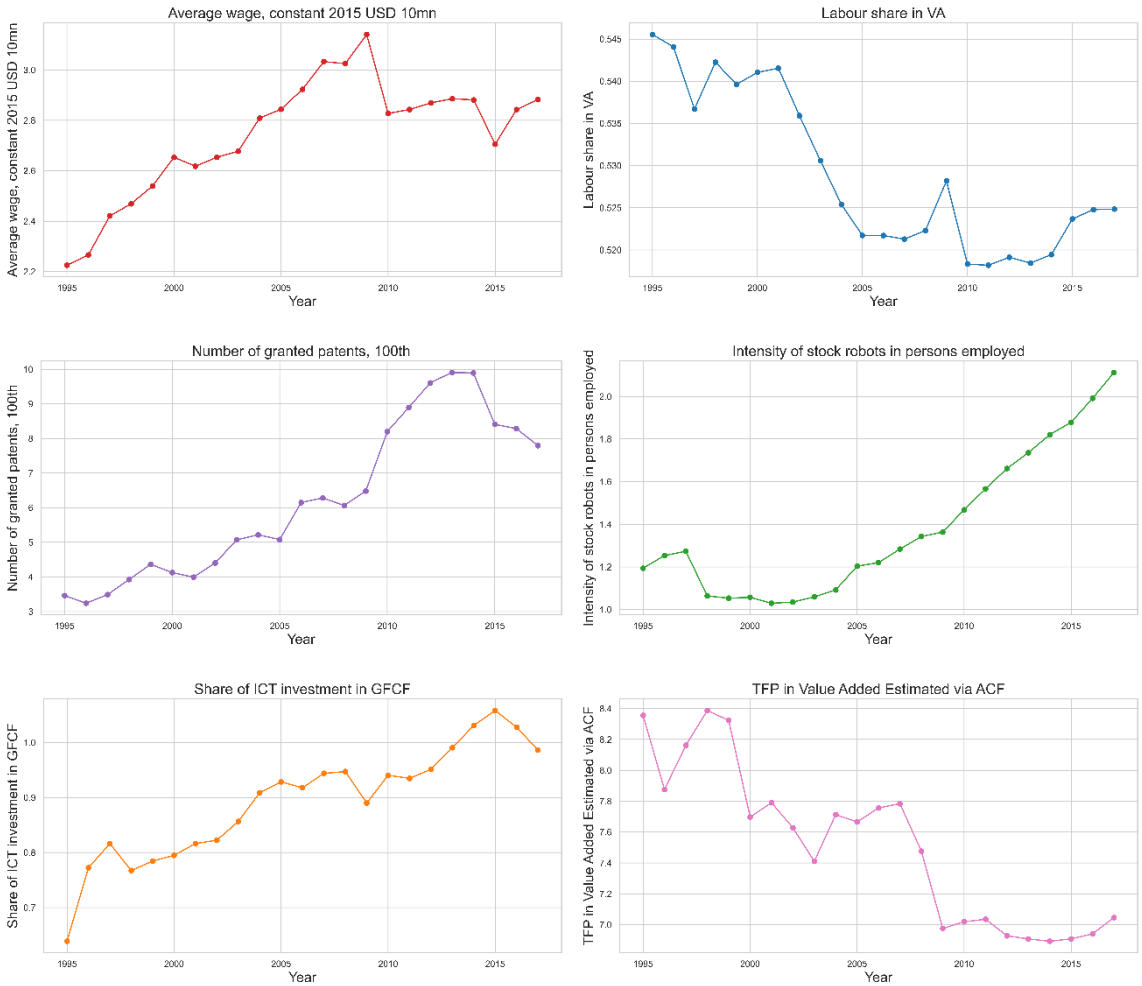
Sources: OECD TiVA, OECD STAN, IFR, authors' elaboration.

**Table C.3 / Correlation matrix of the main explanatory variables used in the analysis**

| | Log of wages | Log of labour income share | Log of number of granted patents | Log of intensity of stock robots in number of persons engaged in total employment | Log of share of ICT investment in GFCF | Log of labour productivity | Log of TFP | Log of capital stock |
|---|---|---|---|---|---|---|---|---|
| Log of wages | 1 | | | | | | | |
| Log of labour income share | 0.0896 | 1 | | | | | | |
| Log of number of granted patents | 0.3137 | 0.0481 | 1 | | | | | |
| Log of intensity of stock robots in number of persons engaged in total employment | 0.1053 | 0.1046 | 0.3354 | 1 | | | | |
| Log of share of ICT investment in GFCF | 0.1092 | 0.1182 | 0.1481 | -0.0293 | 1 | | | |
| Log of labour productivity | 0.4222 | -0.4465 | 0.234 | 0.0876 | 0.0273 | 1 | | |
| Log of TFP | 0.4248 | -0.0364 | 0.0992 | 0.0655 | 0.1517 | 0.5976 | 1 | |
| Log of capital stock | 0.1644 | -0.5513 | 0.0426 | 0.0242 | -0.1337 | 0.7494 | -0.0379 | 1 |

# APPENDIX D

## Figure D.1 / Development of main variables in the sample of study over years



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