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# Essays on Inequality, Automation and Globalisation

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# Author's declaration

I, *Antonio Francesco Gravina* declare that this thesis, titled "Essays on Inequality, Automation and Globalisation", submitted in partial fulfilment of the requirements for the award of Doctor of Philosophy, in the *Department of Economics* at the University of Messina, Italy, is wholly my own work unless otherwise referenced or acknowledged. I certify that:

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# Abstract

The surge of automation technologies and globalisation is fuelling concerns about their potential to cause the disappearance of many traditional jobs and exacerbate disparities. Relatedly, the joint contribution of trade wars, higher robotisation and the ongoing COVID-19 pandemic is exerting additional pressure upon a complete rearrangement of productive activities and spurring an increasingly intense debate. Despite the growing interest, however, the empirical evidence on these topics is far from conclusive. The present Ph.D. dissertation is aimed at contributing to the current debate with three empirical works, tackling the inequality issue. Specifically, *Chapter 1* deals with the determinants of income inequality, relying on a panel of 90 advanced and emerging economies, with data spanning the years 1970-2015. Results show that technology and globalisation are nonlinearly correlated with inequality, depicting U-shaped and inverted U-shaped relationships, respectively. The evidence suggests that these inequality determinants produce opposite effects, depending on threshold values and levels of economic development. *Chapter 2* assesses the impact of advances in robotics, intangible technologies and globalisation on relative wages, following the skill-biased technical change and polarisation of the labour force frameworks. The analysis is performed on data for a panel of 18 mostly European economies and 6 industries over 2008-2017. Main results indicate that intangible technologies and globalisation measures either benefit high-skilled workers or give rise to polarising effects. Finally, *Chapter 3* investigates the existence of robotic capital-skill complementarity, according, among others, to the race between education and technology. Relying on a constructed measure of robotic capital stock, we test the hypothesis of a lower elasticity of substitution between robotic capital and skilled labour. The study is carried out using two OECD country-sector samples and different frameworks, with results pointing to a higher complementarity between robotic capital and skilled labour. Furthermore, we find evidence that robotic and ICT capital equipment produce polarising effects.

In essence, the present work sheds further light on the relevance of automation technologies and globalisation as powerful forces in shaping inequalities. As such, policymakers are called to set suitable measures to address the struggles that workers will face.

# Dedication

*To My Beloved Father . . .*

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CHAPTER 1

# Finance, Globalisation, Technology and Inequality: Do Nonlinearities Matter?[†]


## Abstract

Relying on data for a panel of 90 economies over 1970-2015 and System-GMM estimations, we extend the standard Kuznets-curve empirical framework to investigate how financial development, globalisation and technology affect income inequality. Our findings reveal the presence of significant nonlinearities, consistent with either U-shaped or inverted U-shaped relationships. As such, depending on whether a certain threshold value is achieved, the same determinants of income distribution can exert opposite effects in different countries. Globalisation is associated with increasing inequality in most advanced economies, but to falling disparities for the large majority of emerging economies. Further, while the effects for advanced economies are mixed, technology and financial development lead to increasing inequality for most emerging economies. Hence, particularly in countries in earlier stages of development, policymakers aiming at fostering growth via technological progress or financial development should also consider the nature of the trade-offs with inequality and how policy can improve them.



**Keywords**: Inequality, Globalisation, Technology, Finance, Nonlinearity
**JEL classification**: C01, C33, F63, O11, O15, O33


[†] A preliminary version of this paper, titled "Technology, Nonlinearities and the Determinants of Inequality; New Panel Evidence" and co-authored with Matteo Lanzafame, was presented to the EDEEM Doctoral Summer Workshop in Economics (2019), the $7^{th}$ SIdE-IEA Workshop for PhD students in Econometrics and Empirical Economics (WEEE) and the $60^{th}$ Annual Conference (RSA) of the Italian Economic Association (SIE).

## 1.1 Introduction

The economic determinants of inequality are the subject of a substantial and growing literature, reignited in the last decade by the questions on the causes and consequences of the Great Recession. Though the debate is still open, in recent years economists have reached a significant consensus on the role played by some factors as key drivers of income distribution dynamics: namely, globalisation, financial sector development and technological progress (e.g., Milanović, 2016; Bourguignon, 2017; Nolan *et al.*, 2019). Nonetheless, many questions remain regarding the relative importance of these forces and, therefore, the appropriate policies to achieve a more egalitarian distribution of income without harming economic growth.

The large number of empirical studies in the field rely on different methodologies, estimation techniques and data. Crucially, they also often provide conflicting results – an outcome which may be due to several possible gaps in the existing empirical literature. For instance, most of the available research focuses on the abovementioned three key factors separately, thus providing only a partial view of the sources of inequality. Another estimation issue often not properly considered is variable endogeneity, due to feedback effects from income inequality to its determinants which can be associated with the various channels.[1] Most importantly, lack of a consistent treatment of nonlinearities is an additional critical issue, typically addressed only partially and with respect to individual channels (e.g., Figini and Görg, 2011; Jauch and Watzka, 2016). Nonlinear effects may, among other things, be critical to explain different findings with respect to the same inequality determinants in advanced and emerging economies – as these two groups of countries are typically characterised by a sizeable divide in terms of openness, technology and financial development. For instance, if a minimum degree of financial devel-

[1] Several contributions in the literature have explored the mechanisms via which inequality can influence social and economic outcomes, such as economic growth (Galor and Zeira, 1993; Persson and Tabellini, 1994; Alesina and Rodrik, 1994; Aghion *et al.*, 1999; Barro, 2000; Forbes, 2000; Chen, 2003; Banerjee and Duflo, 2003); the relation between socio-political instability and investments (Alesina and Perotti, 1996); the escape from extreme poverty (Ravallion, 1997); happiness, health and well-being (Easterlin, 1974; Subramanian and Kawachi, 2006; Clark *et al.*, 2008).

opment is required for this driver to reduce (rather than increase) inequality, we may expect financial development to initially lead to greater income disparities in most emerging economies. This also highlights that the presence of significant nonlinearities in the relationship between inequality and its determinants bears relevant policy implications.

Against this backdrop, this paper provides several contributions to the literature on the cross-country determinants of inequality.[2] Relying on a panel of 90 advanced and emerging economies and annual data over 1970-2015, we extend the standard 'Kuznets-curve' (Kuznets, 1955) empirical framework and investigate the role played by technological progress, globalisation and financial sector development, assuming potentially nonlinear effects for all these factors. In so doing, we combine insights from two recent strands of the literature: the first comprises studies considering more than one of the main inequality determinants, but treats their effects as linear (e.g., Jaumotte *et al.*, 2013; Dabla-Norris *et al.*, 2015); the second includes research allowing for nonlinearities, but typically focusing on the various inequality determinants individually (e.g., Figini and Görg, 2011; Nikoloski, 2013). To deal with variable endogeneity and persistence in inequality, estimations are based on dynamic panel data specifications and System-GMM techniques (Arellano and Bover, 1995; Blundell and Bond, 1998). Furthermore, taking account of the issues relating to the ambiguous influence of technological progress, we rely on proxies for two technological categories: Investment-Specific Technology (IST), which influences directly firms' production processes but only indirectly other economic agents; General-Purpose Technology (GPT), which includes technological innovations that, contrary to IST, gradually assume widespread and direct effects on consumers' and other economic agents' incomes.

The key results of the paper support the hypothesis of significant nonlinearities for the main determinants of income inequality, with relations characterised by well-identified extreme points. This outcome has important implications for cross-

[2] Studies focusing on cross-country investigations of inequality drivers include Li *et al.* (1998), Gustafsson and Johansson (1999), Barro (2000), Vanhoudt (2000), Frazer (2006), Roine *et al.* (2009) and Castells-Quintana (2018) for advanced and emerging economies. Further relevant contributions are by Fields (1979), Milanović (2000), Odedokun and Round (2004), and Castells-Quintana and Larrú (2015), which limit the analysis to developing and emerging economies.

country differences in inequality dynamics. Specifically, globalisation, technology and financial development are found to affect income inequality differently depending on whether countries have reached a certain threshold value – as a result, in many cases these same drivers are associated with opposite effects in advanced and emerging economies.

The remaining part of the paper is organised as follows: Section 1.2 presents an overview of the literature; Section 1.3 illustrates the data and the empirical framework used; Section 1.4 presents the estimation results; Section 1.5 investigates further the nature of nonlinearities in the relation between inequality and its determinants, and discusses the implications for advanced and emerging economies. Finally, Section 1.6 concludes.

## 1.2 Overview of related literature

Much of the empirical literature investigating the role of globalisation, technological progress and financial sector development as drivers of inequality leads to mixed results. For instance, focusing on the interplay between globalisation and income inequality, Chen (2007), Gourdon *et al.* (2008) and Helpman *et al.* (2017) observe that greater openness to trade is associated with an increase in wage disparities, whereas Reuveny and Li (2003) and Jaumotte *et al.* (2013) come to the opposite conclusion. Moreover, in the context of financial globalisation, Furceri and Loungani (2018) find evidence of growing income disparities associated with capital account liberalisation reforms, whereas Yu *et al.* (2011) observe a modest impact of foreign direct investment (FDI) on China's regional income inequality. Similarly, conflicting results have emerged for the finance-inequality nexus. Among others, Beck *et al.* (2007), Agnello *et al.* (2012), Hamori and Hashiguchi (2012) and Kappel (2012) provide evidence pointing to a decrease in wage disparities associated with greater financial sector development, while the findings in Jaumotte *et al.* (2013) and Jauch and Watzka (2016) support the opposite hypothesis. Additionally, with specific reference to India, Ang (2010) observes that a well-developed financial system helps to mitigate inequalities, while financial liberalisation exacerbates them.

The available evidence is even less clear-cut when it comes to the role played by technological progress, since different forms of technological innovations are typically difficult to define and measure. Considering the evidence, Iacopetta (2008) points out that price-cutting technological progress is associated with a reduction in inequality, whereas product innovations increase it. Meanwhile, studies on the so-called skill-biased effects of technology provide strong evidence that technological progress raises income inequalities between skilled and unskilled workers (Katz and Murphy, 1992; Goldin and Katz, 2009; Chowdhury, 2010; Acemoglu and Autor, 2011). With specific reference to GPTs, Aghion (2002) find that technology raises long-run within-group inequality boosting demand for adaptable workers and their market premium, whereas Jacobs and Nahuis (2002) observe a fall in real wages for unskilled workers. Meanwhile, He and Liu (2008) argue that IST innovations can explain the rise in wage inequality experienced since the early 1980s in the United States. Further, Krusell *et al.* (2000) find that improvements in ISTs, as proxied by the decline in the relative price of investment goods, increase the wage gap between skilled and unskilled workers. The decrease in the relative price of investment goods is also shown to explain around half of the decline in the labour share of income by Karabarbounis and Neiman (2014).

One possible explanation for the aforementioned inconclusive empirical evidence is linked to nonlinearities, which a number of theoretical contributions have proposed as a key feature of the relationship between inequality an its main drivers.

With respect to globalisation, classic trade theory suggests a clear link between trade and inequality. The Stolper and Samuelson (1941) theorem posits that greater trade openness increases the return of the relatively abundant factor – as such, by spurring specialisation according to comparative advantage, trade leads to falling inequality in emerging economies where low-skilled labour is relatively abundant. For the same reason, trade raises skilled-labour wages and income disparities in advanced economies. Relying on a two-country (North *vis-à-vis* South), two-factor continuum-good model, Xu (2003) shows that these mechanisms may be nonlinear and dependent on the degree of trade openness. Since trade protection makes some potentially-tradable skill-intensive goods nontraded, in his model a tariff reduction has two effects in the South: it expands the import set, implying an inequality-reducing effect by decreasing high-skilled wages; it worsens the South's terms of trade, thus expanding its export set by improving its price competitiveness – this provides an inequality-boosting effect. The export-expansion effect can dominate import expansion, so that a tariff reduction in the South beyond a certain threshold increases both the South's and the North's skilled-labour wages. As a result, there is a U-shaped relationship between wage inequality and the tariff rate – when the tariff rate is below (above) the threshold, further trade liberalisation increases (lowers) wage inequality. Other theoretical approaches, however, postulate the existence of an inverted U-shaped interplay between globalisation and inequality in emerging economies. In this regard, Helpman *et al.* (2010) develop a framework to investigate the determinants of wage distributions focusing on within-industry reallocation, labour market frictions and differences in workforce composition across firms. In their model, changes in trade openness have a nonmonotonic, inverted U-shaped effect on wage inequality – specifically, while disparities are higher in the open-economy equilibrium than in autarky, gradual trade liberalisation first raises and then lowers inequality. This hump-shaped pattern is confirmed by Helpman *et al.* (2017), who extend the model in Helpman *et al.* (2010) to allow for firm heterogeneity in productivity, fixed exporting costs and worker screening. Similarly, Bellon (2018) provides a micro-founded model where, following trade liberalisation, the reallocation dynamics between heterogeneous firms and workers lead to an inverted U-shaped rise in inequality.[3] Meanwhile, focusing on a non-trade aspect of globalisation, Figini and Görg (2011) present a model in which FDI acts as a channel for technological transfers from advanced to emerging economies. The early waves of FDI by multinational enterprises introduce new technologies in the host country, thus widening the wage gap between skilled and unskilled workers. But further waves of FDI allow domestic firms to imitate the multinationals' production technologies, and this is reflected in a reduction of wage disparities.

This FDI-driven diffusion mechanism exemplifies one possible nonlinear link between technology and inequality – but others have also been proposed in the

[3] On the various channels leading to complex skill-biased effects of trade, in particular via outsourcing and offshoring activities, see also Feenstra and Hanson (1996), Glass and Saggi (2001) and Grossman and Rossi-Hansberg (2008) among others.

literature. Theoretical approaches focusing on skill-biased technical change indicate that technological innovations are typically associated with increases in inequality (Katz and Murphy, 1992; Goldin and Katz, 2009; Acemoglu and Autor, 2011). New technologies are assumed to be complementary to high-skilled labour, resulting in higher relative demand for these workers and a growing wage gap between high- and low-skilled labour. Conversely, however, contributions tracing back to Kuznets (1955) suggest that, by disrupting existing sources of wealth, technological progress may also promote a more equal income distribution. Several studies in the literature illustrate how these opposing mechanisms can give rise to a nonlinear relationship between technology and inequality. In particular, theoretical approaches developed by Galor and Tsiddon (1997), Aghion *et al.* (1998), Helpman (1998) and Conceição and Galbraith (2012) result in an inverted U-shaped pattern. The intuition is that, when technology adoption differs between sectors and intersectoral labour mobility is slow and/or imperfect, technological innovations tend to initially raise inequality. This is because only a small number of workers, employed in the technologically-advanced sectors, benefit from innovations. As wages rise and more people move into the advanced sectors, inequality and per-capita GDP both tend to rise. Subsequently, when the gains from technological progress start to be shared more evenly, wage and income disparities gradually shrink too.

Theoretical frameworks developed to investigate the relationship between financial depth and inequality provide a similarly varied picture – with some studies indicating financial development reduces inequality, others pointing to inequality-widening effects and others still supporting an inverted U-shaped relationship. Contributions in the inequality-narrowing camp include Galor and Zeira (1993), who develop a model where economic growth depends on human capital investment and is influenced by the features of capital markets. One of the main results of the study is that, in the presence of financial-market imperfections and tight borrowing constraints for poor households, a country characterised by high income disparities will perpetuate cross-generational differences in human capital investments and inequality, and will grow slower than more egalitarian counterparts. Analogously, Banerjee and Newman (1993) propose a three-sector model with credit constraints in which two of the technologies require indivisible investments. In such a context, higher initial wealth inequality forces poor agents to work for entrepreneurs –

the only agents who can borrow enough to invest and profit from risky but high-return projects. Consequently, both for Galor and Zeira (1993) and Banerjee and Newman (1993), a more developed and inclusive financial sector weakens the link between an individual's initial wealth and entrepreneurship, thus boosting investment and economic growth as well as narrowing income gaps. Contrary to this, several arguments have been proposed to support the inequality-widening hypothesis for financial development. Among others, Lamoreaux (1996), Rajan and Zingales (2003) and Haber (2004) argue that, even in the case of well-functioning financial institutions, only wealthier and politically connected agents will benefit from getting access to credit – so that financial-sector development may exacerbate the rich-poor income divide.[4] Similarly opposing arguments are reconciled by Greenwood and Jovanovic (1990), who show that the relationship between financial development and inequality can follow an inverted U-shaped pattern. These authors propose a model where financial sector development and economic growth are endogenously determined. In the early stages of development, only wealthier agents can afford the high fixed costs of credit to finance their investment projects. This fosters savings and economic growth, but the aggregate income gains come at the expense of a more unequal distribution. In the model, this outcome holds until credit becomes more accessible for a larger part of economic agents. Once a certain threshold financial-development is eventually surpassed, a mature financial sector promotes a more egalitarian income distribution by providing gradually wider access to financial services – so that an increasing share of less-affluent agents can share in the proceeds of growth.

Overall, therefore, while there are several reasons to expect the effects of globalisation, technological change and financial development on inequality to be nonlinear, theory-based predictions regarding the pattern of these nonlinearities are not unambiguous. As a result, this is ultimately an empirical question and in this case too, the available findings are mixed. For instance, in relation to globalisation, Dobson and Ramlogan (2009) and Jalil (2012) highlight the likely

[4] Clarke *et al.* (2006) suggest a further rationale for the positive relation between financial development and inequality. Specifically, being instrumental in fostering the development of more technologically-advanced and unequal sectors, financial development may increase overall income inequality in economies transitioning from traditional to modern production structures.

existence of a curvilinear relationship between international trade and inequality – the 'Openness Kuznets-curve' – for some Latin American countries and China. Moreover, Figini and Görg (2011) find that foreign direct investment has positive effects on wage disparities in advanced economies but a negative impact in emerging economies, noting the presence of an inverted U-shaped curve for this channel. With respect to financial development, empirical evidence supporting the inverted U-shaped hypothesis – the 'Financial Kuznets-curve' – advanced by Greenwood and Jovanovic (1990) has been provided by Clarke *et al.* (2006), Nikoloski (2013) and Jauch and Watzka (2016) both for advanced and emerging economies, as well as by Baiardi and Morana (2018, 2016) for the Euro area. In contrast, findings by Tan and Law (2012) and Brei *et al.* (2018) indicate a U-shaped pattern.

To sum up, while the theoretical literature reveals that each one of these three drivers is likely to have an impact on income inequality via nonlinear mechanisms, most empirical studies are still based on linear specifications and/or examine their effects on inequality separately – thus providing mixed empirical evidence. In what follows, we aim at filling these gaps.

## 1.3 Data and empirical framework

The empirical analysis carried out in this paper is based on a panel of annual data for 90 countries (33 advanced and 57 emerging economies) over the 1970-2015 period.[5] The countries included in the panel and the data sources are reported, respectively, in Tables A.1 and A.2 in the Appendix. We estimate dynamic panel data models relying on a sample of 9 (non-overlapping) five-year periods.[6] The use of five-year averages is common in the panel literature on inequality (e.g., Ostry *et al.*, 2014; Sturm and De Haan, 2015), particularly because it reduces the impact of business cycle effects and data gaps on the estimates. Moreover, averaging is especially useful in studies based on GMM estimation of macro-panels such as ours, since it decreases the likelihood of overfitting by holding down the number of

[5] The time-period of analysis and the countries considered are determined by data availability.
[6] Given that the overall time-series length is 46 years, the last sub-period considers a 6-year average over 2010-2015.

instruments.

Following much of the recent literature (e.g., Jauch and Watzka, 2016; Castells-Quintana, 2018; Baiardi and Morana, 2018), income inequality is measured by the Gini index (*Gini*) based on data from the Standardized World Inequality Database (SWIID). Our baseline models include the following regressors:

- $GDP_{PC}$: *Real GDP per-capita* (in thousands of 2011 US dollars at chained purchasing power parity). $GDP_{PC}$ is included in the analysis to take account of the Kuznets (1955) hypothesis of an inverted-U relationship between income inequality and economic development;

- *EGI*: *Economic Globalisation Index*. Ranging from 0 to 100, with higher values indicating a more globalised economy, EGI summarises the degree of economic and financial globalisation considering the intensity of foreign trade and financial flows, as well as restrictions such as hidden import barriers, customs tariffs and investment limitations. As such, it allows revisiting the issue of nonlinearities in the relationship between inequality and 'openness' (e.g., Dobson and Ramlogan, 2009; Figini and Görg, 2011) taking account of various aspects of globalisation;

- *GPT*: Drawing on the relevant literature, we rely on the following GPT proxies:

  ◇ *Energy Use (tons of oil equivalent per-capita)*. Energy allows the transformation of raw materials into intermediate or final goods, and the direct provision of services for domestic and other uses. Along with these features, its pervasiveness, versatility and widespread availability make of energy use a reliable GPT proxy (e.g., Dalgaard and Strulik, 2011). Moreover, the role played by energy as an engine of industrialisation and economic development (e.g., Mokyr, 1992; Fouquet and Pearson, 1998) suggests a Kuznets-curve type of relation between Energy Use and Gini (e.g., Muller, 1988);

  ◇ *Air Transport, Passengers Carried (per 100 people)*. Air transport has over time evolved into a pervasive technology (Jovanovic and Rousseau, 2005; Lipsey *et al.*, 2005; Ruttan, 2006), underpinning an industry which is now a key driver of economic development, boosting employment, tourism, local businesses and international trade (e.g., OECD, 1997). The available empirical evidence is supportive of a negative correlation between Air Transport and income inequality (e.g., Wu and Hsu, 2012; Li and DaCosta, 2013);

- ⋄ *Mobile Cellular Subscriptions (per 100 people)*. Several studies suggest that, especially in emerging economies, mobile phone penetration can be considered an appropriate proxy for technological progress (e.g., Aker and Mbiti, 2010; Naughton, 2016). In line with the evidence in the literature (e.g., Asongu, 2015), the expected sign on the coefficient for *Mobile Cellular Subscriptions* is negative;

- *IST*: *Relative Price of Investment Goods*. Since IST innovations are expected to reduce the relative price of capital goods, this indicator is commonly used as an IST proxy in the literature (e.g., Krusell *et al.*, 2000). The index is constructed as the ratio of the price level of capital formation to the price level of household consumption, so that a fall in Relative Price of Investment Goods indicates IST progress. IST affects directly only the production side of the economy (e.g., Greenwood *et al.*, 1997; Karabarbounis and Neiman, 2014), so whether it plays a similar role with respect to GPT is an empirical question;

- *FIN*: *Financial Sector Development Index*. *FIN* is defined as private credit (by deposit money banks and other financial institutions) over GDP. The large literature using *FIN* as a proxy for financial sector development provides consistent evidence of an inverted-U relationship with income inequality (e.g., Clarke *et al.*, 2006; Nikoloski, 2013; Jauch and Watzka, 2016).

Descriptive statistics for all variables included in the empirical analysis in the paper are reported in Table 1.1.

### 1.3.1 Panel estimations and econometric issues

Building on the theoretical contributions presented in Section 1.2 and empirical studies by, among others, Jalil (2012), Jaumotte *et al.* (2013) and Nikoloski (2013),

**Table 1.1:** Descriptive statistics

| Variable | No. of observations | Mean | Standard deviation | Minimum | Maximum |
|---|---|---|---|---|---|
| Gini | 623 | 37.262 | 9.459 | 18.25 | 60.2 |
| Economic Globalisation Index | 758 | 54.276 | 16.2 | 12.82 | 93.069 |
| Energy Use (per-capita) | 715 | 2.3 | 2.254 | 0.012 | 17.781 |
| Air Transport (per 100 people) | 720 | 64.193 | 131.33 | 0 | 2072.789 |
| Mobile Cellular Subscriptions (per 100 people) | 773 | 27.865 | 44.284 | 0 | 168.663 |
| Relative Price of Investment Goods | 758 | 0.517 | 0.268 | 0.063 | 1.629 |
| Financial Sector Development | 723 | 48.496 | 39.448 | 0.146 | 246.187 |
| Real GDP per-capita | 758 | 14.507 | 12.922 | 0.436 | 90.497 |
| Rate of Change of Urban Agglomerations | 666 | 1.963 | 1.695 | -3.209 | 8.034 |
| Bureaucracy Quality | 531 | 2.61 | 1.072 | 0 | 4 |
| Human Capital Index | 722 | 2.406 | 0.669 | 1.021 | 3.719 |
| Inflation (annual %) | 724 | 33.307 | 187.313 | -0.516 | 3373.474 |

the benchmark 'Nonlinear' model of our empirical analysis relies on the following dynamic panel specification:

$$\begin{aligned}(GINI)_{i,t} = \alpha_i + \nu_t + \beta_j \sum_{j=1}^{3} (GINI)_{i,t-j} + \gamma_1 EGI_{i,t} + \gamma_2 EGI_{i,t}^2 \\ + \gamma_3 GPT_{i,t} + \gamma_4 GPT_{i,t}^2 + \gamma_5 IST_{i,t} + \gamma_6 IST_{i,t}^2 \\ + \gamma_7 FIN_{i,t} + \gamma_8 FIN_{i,t}^2 + \delta_1 (GDP_{PC})_{i,t} + \delta_2 (GDP_{PC})_{i,t}^2 + \varepsilon_{i,t}\end{aligned} \tag{1.1}$$

where $i = 1,\ldots,N$ and $t = 1,\ldots,T$ indicate, respectively, country and time; $(GINI)_{i,t}$ is our inequality measure; $GPT$ and $IST$ are the two technological progress proxies, i.e. *Energy Use, Air Transport* and *Mobile Cellular Subscriptions* as alternative GPT proxies and *Relative Price of Investment Goods* for IST; $\alpha_i$ indicates fixed effects, $\nu_t$ time dummies, $\varepsilon_{i,t}$ is the error term and all other variables are as defined above.

For comparability purposes, we also consider a simple 'Linear' model where the main drivers of income inequality enter the dynamic panel specification only linearly, except for the terms referring to the Kuznets-curve hypothesis:

$$\begin{aligned}(GINI)_{i,t} = \alpha_i + \nu_t + \beta_j \sum_{j=1}^{3} (GINI)_{i,t-j} + \gamma_1 EGI_{i,t} + \gamma_2 GPT_{i,t} \\ + \gamma_3 IST_{i,t} + \gamma_4 FIN_{i,t} + \delta_1 (GDP_{PC})_{i,t} + \delta_2 (GDP_{PC})^2_{i,t} + \varepsilon_{i,t}\end{aligned} \tag{1.2}$$

As is well known, pooled OLS and fixed effects (FE) estimates of dynamic panel data models are inconsistent due to the dynamic panel bias (Nickell, 1981). This issue is particularly relevant in our case, since Monte Carlo evidence indicates that the Nickell bias may be substantial when the time-series dimension is short (e.g., Judson and Owen, 1999). Additionally, the potential endogeneity of at least some of the regressors raises further concerns regarding the reliability of pooled OLS and FE estimates. To deal with these issues, estimations are carried out using the System-GMM (S-GMM) estimator developed by Arellano and Bover (1995) and Blundell and Bond (1998). Just like the Difference-GMM (Arellano and Bond, 1991) estimator, S-GMM deals with variable endogeneity relying on internal instruments – but it uses both lagged levels and differences of the endogenous variables. Though neither technique has been proven to fully solve endogeneity issues (e.g., Bun and Windmeijer, 2010), these estimators represent a reliable alternative for macro-panel studies such as ours – in the context of which, obtaining valid (and robust) external instruments is very difficult. In our case, S-GMM is preferred over Difference-GMM (Arellano and Bond, 1991) because of its better performance when dealing with highly persistent variables, such as our measure of income inequality (Blundell and Bond, 2000). S-GMM estimations are carried out treating $EGI$, $GPT$ and $IST$ as exogenous variables, while the lags of the dependent variable, $FIN$ and $GDP_{PC}$ are considered as endogenous.

## 1.4 System-GMM estimation results

S-GMM estimates of the dynamic panel data models specified in 1.1 and 1.2 are reported in Table 1.2. For comparability purposes, for each model estimation the results from our baseline 'Nonlinear' specification and from its 'Linear' version are reported in two adjacent columns. This set-up is replicated for the three versions of the baseline model, each one including a different GPT proxy: *Energy Use* for Model v1, *Air Transport* for Model v2 and *Mobile Cellular Subscriptions* for Model v3. For all of the models estimated, the outcome of the Hansen test is in line with the overall validity of the instruments. Furthermore, all tests for first- and second-order autocorrelation of the residuals provide evidence in favour of, respectively, rejection of the AR(1) and no rejection of the AR(2) hypotheses.[7]

Turning to the estimation results, we start by noting that none of the 'Linear' specifications provide evidence of significant effects for the main drivers of inequality. In line with the view that neglecting nonlinearities may produce misleading results, this surprising outcome is completely reversed when the analysis is carried out relying on the 'Nonlinear' specifications – for which the results turn out to be quite different.[8] In particular, the investigation of the role played by technological progress in shaping the dynamics of income inequality provides several relevant insights. Firstly, for the relationship between *Gini* and our IST proxy – *Relative Price of Investment Goods* – we obtain fairly similar results in two out of three estimations (Model v1 and v2), providing evidence of a U-shaped pattern. Note that, since a fall in *Relative Price of Investment Goods* indicates technological progress, this outcome is consistent with theoretical predictions of an inverted U-shaped relation between technology and income inequality (e.g., Aghion *et al.*, 1998; Helpman, 1998). Specifically, the negative and positive signs on, respectively, the linear and quadratic terms of *Relative Price of Investment Goods* indicate that the effects of IST innovations on inequality will depend on whether the relative price of capital is above or below a certain threshold. For countries characterised by a high relative price of capital, the relation between *Gini* and *Relative Price of Investment Goods* is positive – i.e. these countries are located on the right-hand side of the U-shaped

[7] Lag selection was performed with a general-to-specific procedure which, in all cases, indicated the optimal lag length as 3. Lags of the dependent variable Gini turned out to be always strongly significant and the associated coefficients are in line with the expected high degree of persistence in inequality – thus supporting both the adoption of a dynamic panel specification and the S-GMM estimation technique. To save space, the estimated coefficients on the lags of Gini are not reported in the tables of model estimates included in the paper.

[8] This is not the case when the models are estimated relying on the pooled OLS or fixed-effects (FE) estimators, which in most cases return statistically insignificant results for both the Linear and Nonlinear specifications. To save space, the FE estimation results are reported in Table A.3 in the Appendix, while the pooled OLS estimates are available upon request.

curve. In such a case, IST innovations leading to falls in the relative price of capital will be associated with (progressively smaller) declines in income inequality. This is consistent with a scenario in which the positive effects of IST in terms of higher labour productivity and wages outweigh its labour-substituting and skill-biased impact (e.g., Aghion, 2002; Acemoglu and Autor, 2011); when *Relative Price of Investment Goods* is low, the opposite occurs and IST innovations lead to gradually greater rises in inequality. We provide further insights on this point in Section 1.5.

With respect to our GPT proxies, we identify two different outcomes. The relation between *Gini* and *Energy Use* (Model v1), is characterised by an inverted U-shaped pattern in line with model predictions in Galor and Tsiddon (1997) and Aghion *et al.* (1998), among others; by contrast, *Air Transport* (Model v2) and *Mobile Cellular Subscriptions* (Model v3) are characterised by U-shaped relationships with *Gini*. These results confirm that empirical findings on the effects of GPT on inequality should be treated with caution, particularly when based on the use of a single proxy and/or assumed as linear.

For the relationship between *Gini* and the *Economic Globalisation Index* our findings are clear-cut: all the estimated models provide evidence of significant nonlinearities consistent with a U-shaped pattern. This is a somewhat surprising result in contrast with arguments in, for instance, Helpman *et al.* (2017) and the evidence supporting the existence of an 'Openness Kuznets-curve' (e.g., Dobson and Ramlogan, 2009; Jalil, 2012). It is, on the contrary, consistent with standard classical trade theory and model predictions in Xu (2003): globalisation initially reduces inequality by boosting returns to the relatively abundant factor; beyond a certain threshold, however, further liberalisation increases wage inequality as high-skilled workers start to benefit comparatively more from the export-expansion effect. Meanwhile, only one specification (Model v3) provides evidence of a 'Financial Kuznets-curve', i.e. a nonlinear, inverted U-shaped relationship between inequality and *Financial Sector Development* – an outcome in line with, among others, theoretical predictions in Greenwood and Jovanovic (1990) and empirical findings in Nikoloski (2013) and Baiardi and Morana (2018, 2016). Finally, it is worth noting that $GDP_{PC}$ and its square turn out to be not significant in all models – suggesting that the inequality determinants and specifications in Table 1.2 capture appropriately the mechanisms proxied by the per-capita GDP terms in the standard Kuznets-curve framework.

**Table 1.2:** S-GMM regression results: Dependent variable is Gini Coefficient

| | Model v1 | | Model v2 | | Model v3 | |
|---|---|---|---|---|---|---|
| | Linear | Nonlinear | Linear | Nonlinear | Linear | Nonlinear |
| Economic Globalisation Index | -0.0061 | -0.1660** | -0.0087 | -0.2024*** | 0.0019 | -0.2521** |
| | (0.0153) | (0.0679) | (0.0150) | (0.0567) | (0.0134) | (0.1217) |
| (Economic Globalisation Index)$^2$ | | 0.0013** | | 0.0016*** | | 0.0019* |
| | | (0.005) | | (0.004) | | (0.0010) |
| Energy Use | -0.0617 | 0.3370** | | | | |
| | (0.0911) | (0.1381) | | | | |
| (Energy Use)$^2$ | | -0.0250** | | | | |
| | | (0.0106) | | | | |
| Air Transport | | | -0.0011 | -0.0089*** | | |
| | | | (0.0014) | (0.0031) | | |
| (Air Transport)$^2$ | | | | 0.0000** | | |
| | | | | (0.0000) | | |
| Mobile Cellular Subscriptions | | | | | 0.001 | -0.0232** |
| | | | | | (0.0051) | (0.0116) |
| (Mobile Cellular Subscriptions)$^2$ | | | | | | 0.001* |
| | | | | | | (0.0001) |
| Relative Price of Investment Goods | 0.9163 | -6.1547* | 0.7865 | -9.1556** | 0.6902 | 3.6106 |
| | (0.7866) | (3.3088) | (0.7061) | (3.7221) | (0.9202) | (3.3781) |
| (Relative Price of Investment Goods)$^2$ | | 4.3819** | | 5.8131** | | -1.6525 |
| | | (2.1642) | | (2.5629) | | (1.5966) |
| Financial Sector Development | -0.0007 | 0.0072 | 0.0006 | 0.0226* | 0.0052 | 0.0296* |
| | (0.0033) | (0.0104) | (0.0035) | (0.0127) | (0.0040) | (0.0152) |
| (Financial Sector Development)$^2$ | | -0.0000 | | -0.0001 | | -0.001* |
| | | (0.0001) | | (0.0001) | | (0.0001) |
| Real GDP per-capita | -0.0214 | -0.0380 | -0.0160 | 0.0379 | -0.0596 | -0.0409 |
| | (0.0312) | (0.0325) | (0.0320) | (0.0324) | (0.0397) | (0.0508) |
| (Real GDP per-capita)$^2$ | 0.0003 | 0.0002 | 0.0003 | -0.0002 | 0.0006 | 0.0001 |
| | (0.0003) | (0.0003) | (0.0003) | (0.0003) | (0.0004) | (0.0005) |
| No. Observations | 350 | 350 | 336 | 336 | 352 | 352 |
| No. Groups | 84 | 84 | 83 | 83 | 83 | 83 |
| No. Instruments | 65 | 76 | 68 | 79 | 64 | 62 |
| Time effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Hansen test ($p$-value) | 0.3754 | 0.3830 | 0.5444 | 0.8618 | 0.2507 | 0.3845 |
| AR(1) | 0.0055 | 0.0043 | 0.0031 | 0.0025 | 0.0063 | 0.0334 |
| AR(2) | 0.2613 | 0.2380 | 0.2381 | 0.3628 | 0.3209 | 0.4043 |

*Notes*: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. Estimates are based on dynamic panel data estimation, using data averaged over five-years periods and two-step System-GMM. All models instrument as endogenous the dependent variable, financial sector development and real GDP per-capita. Time dummies are included as strictly exogenous instruments in the level equations for all specifications. Fixed-effects are removed via the forward orthogonal deviation (FOD) transformation and all models are estimated with Windmeijer (2005) finite sample correction; $p$-values are reported for Hansen, AR(1) and AR(2) tests.

### 1.4.1 Robustness analysis

To assess the robustness of the results in Table 1.2, we now extend the model specifications using a number of control variables usually considered as possible additional determinants of inequality in the literature. Specifically, we include the following variables:

- *Rate of Change of Urban Agglomerations*. Urbanisation can play a relevant role in determining inequality dynamics at the country level.[9] Due to agglomeration economies and other externalities, cities are typically characterised by economic and job opportunities unevenly distributed in space. As a result, larger cities are generally richer but also more unequal than smaller cities and rural areas. All else constant, therefore, growing urban areas are likely to be associated with increasing inequality (United Nations, 2020). Following Castells-Quintana (2018), we control for potentially nonlinear effects of urbanisation relying on the annual average growth rate of urban agglomerations above 300,000 inhabitants within the same country;[10]

- *Human Capital*. Retrieved from the Penn World Tables, this index is constructed using average years of schooling from Barro and Lee (2013) and an assumed rate of return to education, based on Mincer-equation estimates around the world (Psacharopoulos, 1994). Evidence on the effects of human capital accumulation is ambiguous, as some studies link it to decreasing income disparities (e.g., Dabla-Norris *et al.*, 2015) while others find it widens the wage gap via skill-premium effects (e.g., Park, 1996; Goldin and Katz, 2009);

- *Bureaucracy Quality*. Constructed by the International Country Risk Guide, the index ranges between 0 and 4. Higher values correspond to lower-risk countries, where bureaucracy is more transparent and independent from

[9] Recent urban economics literature pointed out that further drivers of income inequality can be traced to the city level (e.g., Behrens and Robert-Nicoud, 2014; Sarkar *et al.*, 2018) as well as to the regional level (e.g., Perugini and Martino, 2008; Castells-Quintana and Larrú, 2015).

[10] Rather than in growth-rate form, Castells-Quintana (2018) uses the same proxy for urban agglomeration in levels: the latter turns out to be not significant in our case.

political pressures. This indicator is often used as a proxy for institutional quality, which can be expected to mitigate income disparities (e.g., Chong and Gradstein, 2007);

- *Inflation (annual %)*. Higher inflation is expected to increase income inequality, as its harmful consequences typically affect to a larger extent the poor- and the middle-class (e.g., Erosa and Ventura, 2002; Albanesi, 2007).

Table 1.3 presents the S-GMM estimation results for the extended model specifications. Two important conclusions reached in the previous section prove to be robust to all three versions of the extended 'Nonlinear' models. The first, which is common to all estimations in Table 1.2, is the statistically significant U-shaped relationship between *Gini* and the *Economic Globalisation Index*. The second is that Investment-Specific Technology plays a prominent role as a determinant of inequality dynamics: *Relative Price of Investment Goods* turns out to be always significant and its U-shaped nonlinear effects are confirmed. Meanwhile, the significant but mixed evidence reported in Table 1.2 for the effects of GPT turns out not to be robust to the inclusion of additional controls – an outcome that reinforces the notion that IST plays a more important role than GPT as a driver of inequality trends. Moreover, just as in Table 1.2, there is only partial evidence (Model v5) supporting the hypothesis that *Financial Sector Development* affects inequality.

Turning to the additional control variables included in the robustness analysis, there is a persistent outcome to highlight. The relationship between *Gini* and the *Rate Change of Urban Agglomerations* is characterised by an inverted U-shaped pattern for all the estimated models. This is consistent with the hypothesis that faster-growing cities lead to increasing inequality (United Nations, 2020) but, beyond a certain threshold, the benefits from growing urbanisation outweigh its inequality-boosting effects. Finally, while *Inflation* turns out to be not significant, we find only limited evidence that *Human Capital* (Model v6) and *Bureaucracy Quality* (Model v5) play a role in, respectively, increasing and reducing income inequality.

Overall, therefore, the empirical findings in this section give a clear-cut answer to the questions on the relative importance of the main determinants of inequality. Specifically, the data support the hypothesis of empirically robust effects on

**Table 1.3:** S-GMM robustness checks results: Dependent variable is Gini Coefficient

| | Model v4 | | Model v5 | | Model v6 | |
|---|---|---|---|---|---|---|
| Economic Globalisation Index | -0.2545*** | (0.0867) | -0.2773*** | (0.0968) | -0.2854*** | (0.1052) |
| (Economic Globalisation Index)$^2$ | 0.0020** | (0.0008) | 0.0022*** | (0.0008) | 0.0023** | (0.0009) |
| Energy Use | 0.0841 | (0.5370) | | | | |
| (Energy Use)$^2$ | 0.0034 | (0.0353) | | | | |
| Air Transport | | | -0.0055 | (0.0051) | | |
| (Air Transport)$^2$ | | | 0.0000 | (0.000) | | |
| Mobile Cellular Subscriptions | | | | | 0.0041 | (0.0190) |
| (Mobile Cellular Subscriptions)$^2$ | | | | | -0.0001 | (0.0001) |
| Relative Price of Investment Goods | -13.1907*** | (4.2884) | -13.8460*** | (5.1508) | -11.9049** | (5.7214) |
| (Relative Price of Investment Goods)$^2$ | 7.9398*** | (2.6504) | 8.5532** | (3.3576) | 7.0210** | (3.4940) |
| Financial Sector Development | 0.0266 | (0.0199) | 0.0374*** | (0.0131) | 0.0218 | (0.0165) |
| (Financial Sector Development)$^2$ | -0.0001 | (0.0001) | -0.0002** | (0.0001) | -0.0001 | (0.0001) |
| Real GDP per-capita | -0.0348 | (0.0752) | 0.0440 | (0.0619) | -0.0252 | (0.0673) |
| (Real GDP per-capita)$^2$ | -0.0002 | (0.0008) | -0.0004 | (0.0007) | -0.0003 | (0.0008) |
| Rate of Change of Urban Agglomerations | 0.6788* | (0.4006) | 0.5766** | (0.2873) | 0.8568** | (0.4280) |
| (Rate of Change of Urban Agglomerations)$^2$ | -0.1718* | (0.0956) | -0.1564*** | (0.0525) | -0.2129** | (0.0869) |
| Bureaucracy Quality | -0.3892 | (0.3281) | -0.5438* | (0.2749) | -0.4983 | (0.3173) |
| Human Capital | 0.8503 | (0.7705) | 0.4377 | (0.5931) | 1.3274* | (0.7549) |
| Inflation (annual %) | 0.0005 | (0.0015) | -0.0003 | (0.0012) | 0.0006 | (0.0015) |
| No. Observations | 320 | | 309 | | 320 | |
| No. Groups | 72 | | 72 | | 72 | |
| No. Instruments | 67 | | 69 | | 69 | |
| Time effects | Yes | | Yes | | Yes | |
| Hansen test (*p*-value) | 0.7798 | | 0.9004 | | 0.5890 | |
| AR(1) | 0.0105 | | 0.0116 | | 0.0103 | |
| AR(2) | 0.4611 | | 0.7354 | | 0.5879 | |

*Notes*: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. Estimates are based on dynamic panel data estimation, using data averaged over five-years periods and two-step System-GMM. All models instrument as endogenous the dependent variable, financial sector development, real GDP per-capita and the rate of change of urban agglomerations. Time dummies are included as strictly exogenous instruments in the level equations for all specifications. Fixed-effects are removed via the forward orthogonal deviation (FOD) transformation and all models are estimated with Windmeijer (2005) finite sample correction; *p*-values are reported for Hansen, AR(1) and AR(2) tests.

inequality for globalisation and investment-specific technological progress. On the contrary, there is only non-robust and/or limited evidence indicating significant effects for GPT and financial development. Moreover, our investigation brings qualified support to the view that empirical analyses of inequality determinants should be cast within a comprehensive framework – taking account of all the main drivers of inequality and, in particular, their potentially nonlinear effects. The presence of different types of nonlinearities in the relationships between inequality and its main drivers is a relevant matter from a policy perspective, as it adds a new dimension of complexity to the traditional trade-off between efficiency and equity. In this respect, therefore, our findings deserve further scrutiny.

## 1.5 Testing for monotonicity in nonlinear relationships

When both economic growth and a more equal distribution of income are policy objectives, trade-offs can arise because growth-boosting policies – such as incentives for R&D expenditure or trade liberalisation measures – may result in rising income inequality via several channels, including skill-premium effects and the adoption of labour-substituting technology. For instance, such a trade-off exists when the nonlinear relationship between income inequality and globalisation is characterised by a well-identified minimum – as suggested by the estimates in Tables 1.2 and 1.3. In such a case, while globalisation initially fosters a more equal income distribution, the inequality-reducing effects of additional liberalisation measures become gradually smaller and, beyond a certain threshold value, the relationship changes sign and further integration in the global economy starts exacerbating inequality. On the contrary, when the relationship is nonlinear but also monotonic there exists no clear threshold beyond which further globalisation raises inequality: thus, there is no clear policy trade-off either. For these reasons, a formal assessment of whether the nonlinear relationships uncovered in the previous section are characterised by well-defined extreme points, i.e. a minimum or maximum within the data range, is critical for policy purposes.

To further investigate this issue, we rely on the test for U-shaped relationships proposed by Lind and Mehlum (2010) (hereafter 'LM test').[11] These authors point out that estimation of quadratic specifications may inaccurately yield an extreme point and, therefore, indicate U-shaped patterns when the true relationships are in fact characterised by convexity as well as monotonicity. In order to obtain reliable extreme points, and thus correct (inverted) U-shaped structures, the LM test

[11] Among others, the LM test is employed by Arcand *et al.* (2015) and Leonida *et al.* (2015) to assess the nonmonotonic impact of, respectively, financial depth and political competition on economic growth.

checks whether the nonlinear relationship is (increasing) decreasing at low values and (decreasing) increasing at high values within the data range. In such a case, rejection of the null hypothesis of monotonicity would provide evidence in favour of (inverted) U-shaped relationships.

In this section, we carry out LM tests for U-shaped structures in Model v5 – the only specification in Table 1.3 providing consistent evidence of significant nonlinearities not only for *Economic Globalisation Index*, *Relative Price of Investment Goods* and *Rate of Change of Urban Agglomerations*, but also for *Financial Sector Development*.[12] The results in Table 1.4 are clear-cut and indicate that, in all cases, the nonlinear relationships between *Gini* and its relevant determinants are characterised by the presence of well-identified extreme points. The null hypothesis of monotonicity is systematically rejected at the 5 percent significance level in favour of U-shaped patterns for $EGI$ and *Relative Price of Investment Goods*, and inverted-U shapes for *Financial Sector Development* and the *Rate of Change of Urban Agglomeration*. As such, the LM test results are consistent with the existence of well-defined threshold values beyond (or below) which the impact of the drivers of inequality changes sign.

These findings can be used to provide useful insights in terms of cross-country differences for the effects of inequality determinants, as we can establish where countries are located with respect to the thresholds – an exercise we carry out comparing the (most recent) 2010-2015 averages of the relevant variables to the estimated turning points.[13] For instance, with respect to globalisation we find that for 31 out of 65 countries the 2010-2015 average of the *Economic Globalisation Index* is higher than the estimated threshold value of 64.4, which indicates the turning point in the U-shaped relationship with *Gini* (Table 1.4). These countries are, thus, characterised by a positive relationship between globalisation and inequality (Figure 1.1). Interestingly, among these are 22 advanced economies out of a total of 24. On the contrary, 78 percent of emerging economies (32 out of 41) are

[12]The LM test results for the other specifications in Table 1.3 reflect closely the findings obtained for Model v5. These additional results are not reported here for reasons of space, but are available upon request.

[13]Due to gaps in the data, relying on the 2010-2015 averages as reference values for the comparisons with the estimated thresholds reduces the sample from 72 to 65 countries.

**Table 1.4:** Tests for U-shape and Inverse U-shape: Model v5

| Relationship | Gini and Economic Globalisation Index | | Gini and Relative Price of Investment Goods | | Gini and Financial Sector Development | | Gini and Rate of Change of Urban Agglomerations | |
|---|---|---|---|---|---|---|---|---|
| | *Min* | *Max* | *Min* | *Max* | *Min* | *Max* | *Min* | *Max* |
| Slope at | -0.222 | 0.123 | -12.767 | 14.019 | -0.037 | -0.055 | 1.580 | -1.937 |
| $t$-value | -2.904 | 2.169 | –2.695 | 2.340 | 2.856 | -2.090 | 2.657 | -3.065 |
| $p$-value | 0.002 | 0.016 | 0.004 | 0.011 | 0.002 | 0.020 | 0.004 | 0.001 |
| Test | H1: U shape vs. H0: Monotone or Inverse U shape | | H1: U Shape vs. H0: Monotone or Inverse U shape | | H1: Inverse U shape vs H0: Monotone or U shape | | H1: Inverse U shape vs. H0: Monotone or U shape | |
| Overall significance | 2.170 | | 2.340 | | 2.090 | | 2.660 | |
| $p$-value | 0.016 | | 0.0011 | | 0.0020 | | 0.0004 | |
| Extreme point | 64.45 | | 0.809 | | 99.601 | | 1.842 | |
| Confidence interval | [56.795; 85.152] | | [0.672; 1.131] | | [75.422; 210.582] | | [0.026; 3.034] | |

*Notes*: The confidence intervals are calculated by the Fieller method.

positioned to the left of the $EGI$ threshold in Figure 1.1. Thus, for these economies a growing degree of globalisation will be associated with falling income disparities. This outcome is consistent with a significant part of the literature which, in line with the predictions of classic trade theory, indicates that globalisation has affected negatively the incomes of low-skilled workers in advanced economies while benefiting the poor in emerging economies (e.g., Wood, 1995).

Similarly, given the U-shaped structure underpinning the relationship between *Gini* and *Relative Price of Investment Goods*, we find that 13 advanced economies are located to the right of the estimated threshold value (0.81) in Figure 1.2. For these economies, technological progress (as reflected by a fall in the relative price of capital) will lead to gradually smaller declines in inequality. In this respect, a striking outcome is that this is also true for only 2 emerging economies (Armenia and Kazakhstan) in our panel. For the other 39 emerging and 11 advanced economies located to the left of the threshold value for *Relative Price of Investment Goods*, the implication is that IST innovations will lead to rising income disparities. As technological progress is the main driver of long-run growth, this finding for emerging economies is consistent with the classic Kuznets-curve hypothesis that economic development will be associated with growing income disparities in its

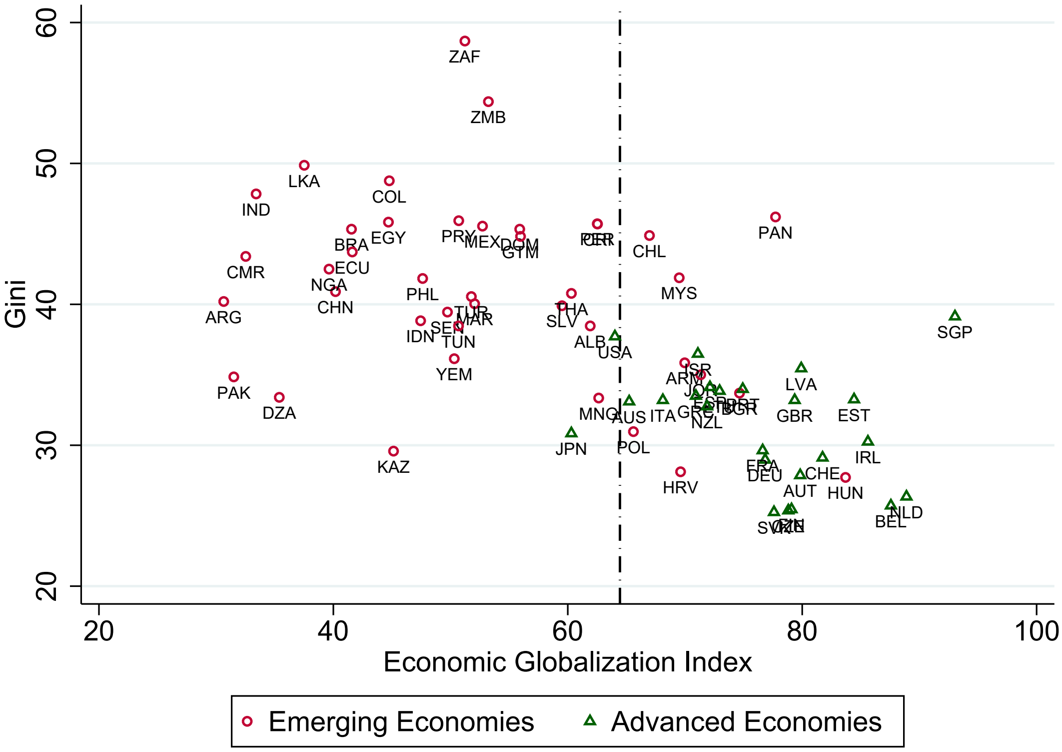



Figure 1.1: Location of advanced and emerging economies with respect to the estimated threshold value for *Economic Globalisation Index*.

earlier stages.

For the inverted U-shaped relationship between *Gini* and *Financial Sector Development*, the turning point is estimated at a level of private credit over GDP of 99.6 percent. With respect to the latter, the advanced economies are equally split: 12 are located to the right of the threshold and are characterised by a negative relation between inequality and financial development, while the opposite is true for the remaining 12. Once again, however, the results are significantly different for emerging economies as only 5 are located to the right of the threshold in Figure 1.3. That is, for the vast majority (88 percent) of the emerging economies in our panel, *Financial Sector Development* is associated with an increase in *Gini*. This outcome is in line with other evidence in the literature (e.g., Nikoloski, 2013; Jauch and Watzka, 2016) and supports the hypothesis that a minimum level of financial

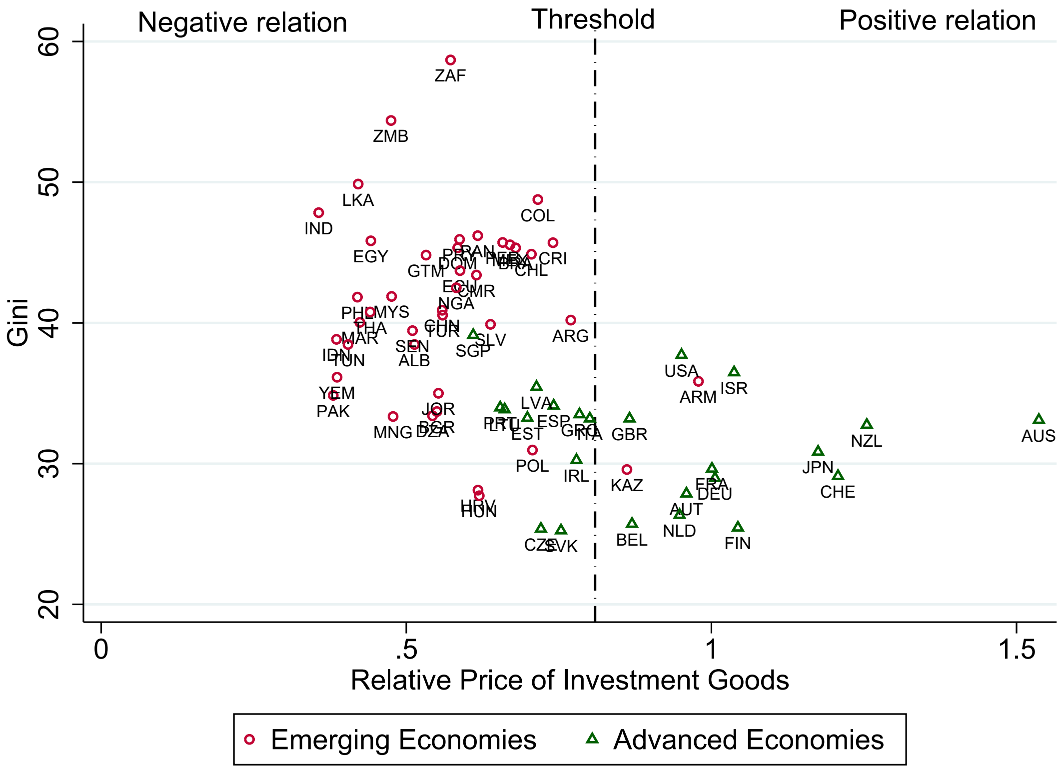



Figure 1.2: Location of advanced and emerging economies with respect to the estimated threshold value for *Relative Price of Investment Goods*.

development is required for this driver to reduce inequality.

Finally, for the inverted U-shaped interplay between inequality and urbanisation, the estimated threshold value for *Rate of Change of Urban Agglomerations* is 1.85 percent. With respect to this, the majority of emerging economies (26) are located in the right-hand side of Figure 1.4, where faster urbanisation is associated with falling inequality. This is consistent with the view that the large expected returns triggering rural-urban migration and growing urbanisation in emerging economies do translate in many cases in better incomes for low-skilled workers, thus acting as an inequality-reducing mechanism (e.g., Todaro, 1969; Nord, 1980). On the contrary, with the marginal exception of Australia and Israel, for 22 out of 24 advanced economies faster city growth is associated with growing inequality. Among others, this is in line with arguments in Behrens and Robert-Nicoud

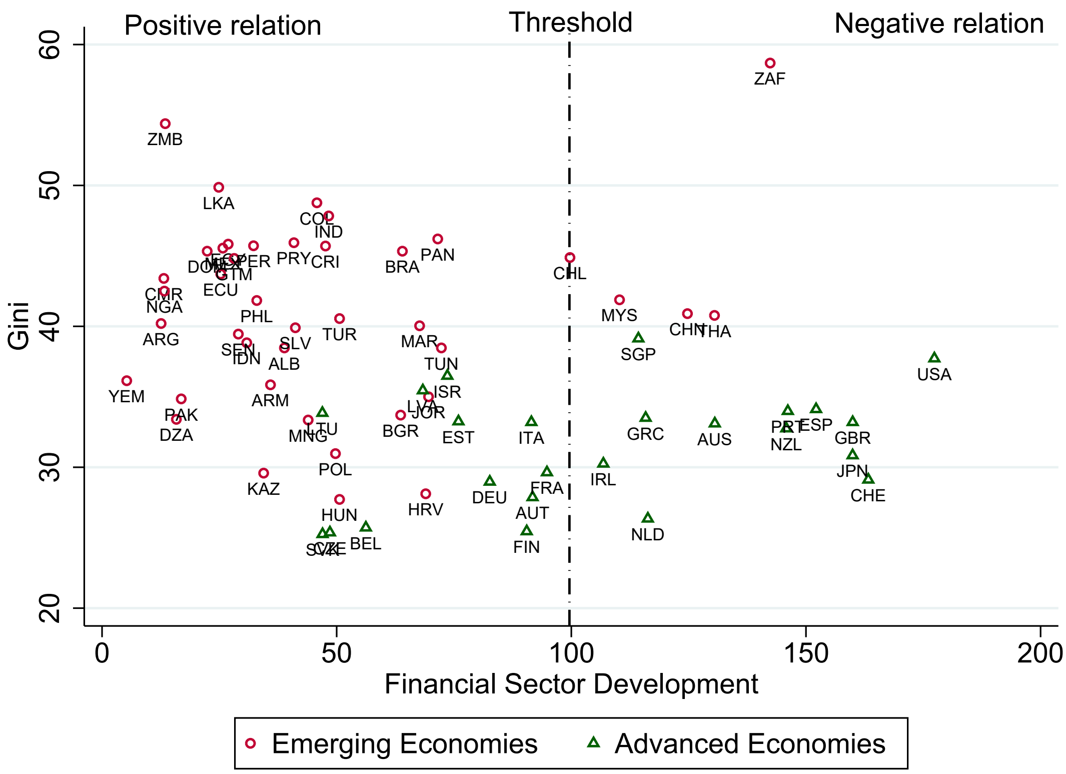



Figure 1.3: Location of advanced and emerging economies with respect to the estimated threshold value for *Financial Sector Development*.

(2014) and Castells-Quintana and Royuela (2014) indicating that, due to stronger agglomeration effects leading to a relatively more developed business environment and larger shares of high-skilled labour, in advanced economies inequality can be expected to increase with urbanisation.

To sum up, the results in this section provide a clear indication that the presence of significant nonlinearities has important implications for the relationship between income inequality and its main determinants. In particular, because of the nonlinear nature of the relation, policy trade-offs may turn out to be substantially different in advanced *vis-à-vis* emerging economies.

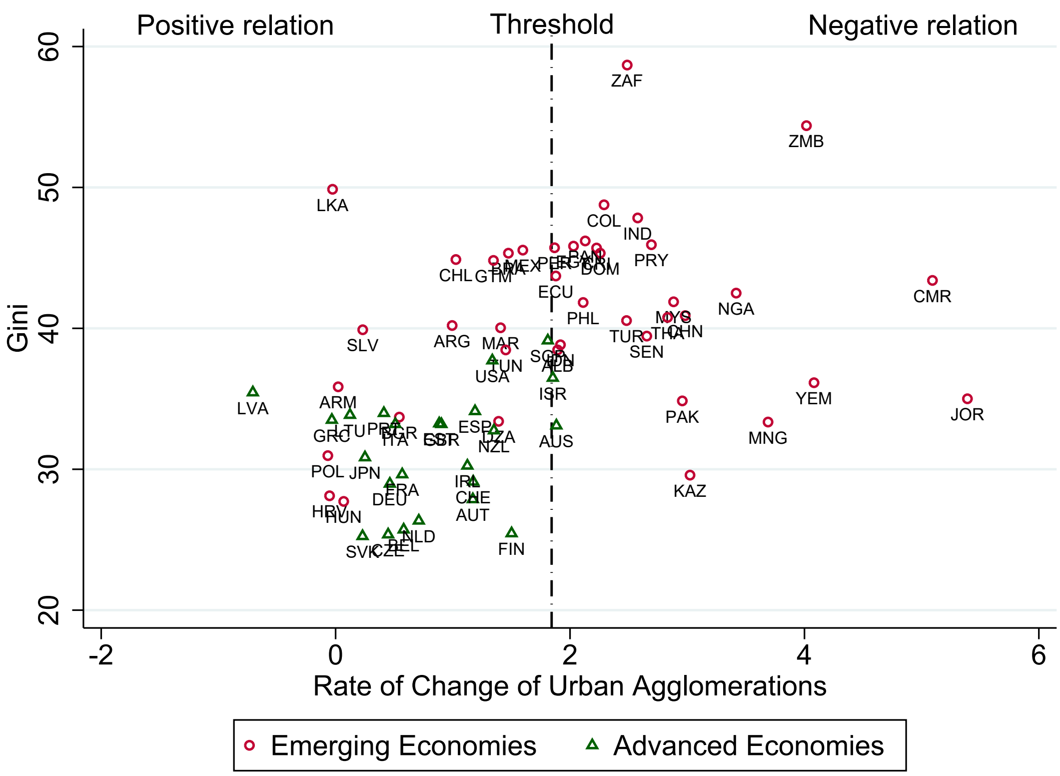



Figure 1.4: Location of advanced and emerging economies with respect to the estimated threshold value for *Rate of Change of Urban Agglomerations*.

## 1.6 Conclusions

Relying on a panel dataset of annual data over the 1970-2015 period for 90 advanced and emerging economies, this paper carries out an empirical investigation of the determinants of inequality dynamics. We pay special attention to the role played by financial sector development, globalisation and technology, modelling their impact as potentially nonlinear. To take account of persistence in inequality and variable endogeneity, the empirical analysis is based on System-GMM estimations.

Our findings point to the presence of significant nonlinearities and, relying on a formal testing approach developed by Lind and Mehlum (2010), we find that the nonlinear relationships between inequality and its determinants are characterised by well-identified extreme points within the data range. This outcome indicates that the relations are non-monotonic – i.e. of either U-shaped or inverted-U shaped type – and thus subject to threshold behaviour. This has important implications for cross-country differences in inequality dynamics. Using the estimated threshold values, we show that technological progress and financial sector development are associated with increasing inequality for most emerging economies, while advanced economies turn out to be fairly evenly located on both sides of the estimated thresholds for these two determinants of inequality. Meanwhile, with respect to the role played by globalisation and urbanisation our results provide evidence of a stark contrast between advanced and emerging economies – that is, while for the large majority of emerging economies increasing globalisation and urbanisation lead to falling income disparities, they are associated with increasing inequality for most advanced economies.

Overall, therefore, our findings suggest that the mixed evidence in the literature on the role played by inequality drivers can be explained (at least to some extent) by the presence on nonlinear effects. The important implication is that the same determinants can exert opposite effects on inequality in advanced and emerging economies, as a result of the significant differences characterising these two country groups – in particular, in terms of financial development, globalisation and technology. This is especially relevant for policymakers in countries in the earlier stages of development, where policies fostering crucial engines of growth such as technological progress and financial development can also lead to worsening income inequality. Further research is needed to better understand the changing nature of these trade-offs at the individual country level, and how policy can improve them.

CHAPTER 2

# AUTOMATION, GLOBALISATION AND RELATIVE WAGES: AN EMPIRICAL ANALYSIS OF WINNERS AND LOSERS[‡]


## Abstract

In this paper, we study the effects of advances in robotics, tangible and intangible technologies, and trade openness and global value chain participation on relative wages, relying upon the skill-biased technical change and polarisation of the labour force frameworks. The empirical analysis is carried out using a panel dataset comprising 18 mostly advanced European economies and 6 industries, with annual observations spanning the period 2008-2017. Our findings suggest that intangible technologies – especially software & databases – significantly increase the wage premium for high- relative to lower-skilled labour. Additionally, the tangible component of ICT primarily benefits lower-skilled workers, whereas R&D and trade openness produce polarising effects. The results are robust to the inclusion of sector-specific labour market regulations variables in the models.



**Keywords**: Robots, Intangibles, Automation, ICT, Globalisation, Wage Differentials

**JEL classification**: C01, F16, F63, J31, O11, O33, O43


[‡] A co-authored version of this work, written together with Neil Foster-McGregor, is avilable at: `https://www.merit.unu.edu/publications/working-papers/abstract/?id=8622`.

## 2.1 Introduction

We are witnessing an increasingly intense debate centred around the impact of artificial intelligence, automation technologies and robotics on economic growth, inequality and society as a whole. Economists, analysts, journalists and policymakers are split on the consequences of the introduction of these new technologies, with both optimists and pessimists. The former argue that, in the next decades, we will see a boost in productivity and new job opportunities, most of which are currently hard to envisage (e.g., Brynjolfsson and McAfee, 2014; Baldwin, 2019), while the latter predict significant job destruction and a sharp increase in income inequality (e.g., Freeman, 2015; Frey and Osborne, 2017; Berg *et al.*, 2018).

While efforts have been made on the theoretical front to understand the mechanisms through which new technologies are shaping the functioning of modern labour markets (see, for instance, Acemoglu and Restrepo, 2019, 2018b; Nakamura and Zeira, 2018), the empirical evidence is far from conclusive. For instance, in a panel of 17 advanced economies, Graetz and Michaels (2018) observe a positive correlation between the use of industrial robots and growth in both employment and total factor productivity, but also a decline in the employment share of low-skilled workers. On the contrary, Acemoglu and Restrepo (2020) show that robots had a negative impact on employment and wages within the US.

By focussing on robots, these studies capture only the 'tangible' or 'embodied' part of technical change (e.g., Greenwood *et al.*, 1997; Hercowitz, 1998), with employment, productivity and wages being affected as a result of investment in new machinery. In recent years, interest has arisen in assessing the contribution of specific forms of investments previously not well acknowledged and measured, i.e. intangible assets (e.g., McGrattan and Prescott, 2010, 2014). Consequently, researchers have questioned whether the labour-market effects of 'intangible' technical change (e.g., Corrado *et al.*, 2009; Haskel and Westlake, 2018), such as software and R&D, affect workers in a similar manner to tangible investments or not. In this respect, for instance, Blanas *et al.* (2019) provide evidence in support of the hypothesis that software displaced medium- and low-skilled workers, whereas Michaels *et al.* (2014) point out a polarising, negative impact of R&D on the share of the wage bill captured by medium-skilled labour. Furthermore, as stressed by

Haskel and Westlake (2018), the impact of intangibles is expected to lead to a rising premium for well-educated workers, insofar as specific education and skills are required for managing these new technologies. The overall outcome, therefore, may depend on how the two types of technical change – i.e., broken down into tangible and intangible capital assets – affect different kinds of workers, either enhancing or mitigating their relative importance in the production process.

Relatedly, the existing empirical studies in this field are typically focused on the impact of automation technologies, neglecting the potentially relevant role played by trade and particularly participation in Global Value Chains (GVCs) in determining labour market outcomes. In this regard, as pointed out by Van Reenen (2011), trade with low-wage countries could force firms in advanced economies to "innovate or die" – producing, among others, significant impacts on the skill structure of labour demand, wages and productivity (e.g., Wood, 1995; Michaels *et al.*, 2014; Lopez Gonzales *et al.*, 2015).

Finally, the contributions of labour market institutions in affecting wage differentials deserves particular scrutiny, with such institutions producing significant effects on living standards, productivity and social cohesion, especially in European economies (e.g., Koeniger *et al.*, 2007; Betcherman, 2012).

Building on these considerations and the mixed empirical evidence on the role played by automation technologies and globalisation, we fill the gaps in the literature by investigating the effects of both advances in robotics, tangible and intangible technologies, trade, and labour market institutions on relative wages, relying on the skill-biased technical change and polarisation frameworks (e.g., Autor *et al.*, 2006; Goos and Manning, 2007; Goldin and Katz, 2009; Goos *et al.*, 2009; Acemoglu and Autor, 2011). In terms of data, the research carried out in this paper relies on a panel of 18 mostly advanced European economies and 6 industries, using annual data over the years 2008-2017. In performing the empirical investigation, we exploit the new EU KLEMS (2019) database, which explicitly groups fixed capital stocks into tangible and intangible assets, according to Haskel and Westlake (2018). Additionally, by integrating data on operational stocks of industrial robots from the International Federation of Robotics (IFR), we have the opportunity to detect the influence of advances in robotics, ICT, R&D and Software & Databases as different, independent proxies for tangible and intangible technologies, respectively. To disentangle the effects of the aforementioned drivers on relative wages, we simultaneously estimate a system of wage premium equations by making use of seemingly unrelated regressions to deal with correlations in the error terms across equations. Thereby, this study fits into different strands of the literature: from the skill-biased technical change and polarisation frameworks to the impact of automation technologies, international trade and institutions on labour market outcomes.

One of the main messages of this paper is that breaking down technology into tangible and intangible components allows for a clearer understanding of how technological changes impacts the skill-premia. For instance, intangible technologies, such as Software & Databases, produce greater advantages to well-educated labour. By contrast, less-qualified workers seem to be able to benefit more from the tangible component of ICT. The analysis also highlights the role played by international trade and labour market institutions in the dynamics of wage differentials.

The paper is structured as follows: Section 2.2 reviews the relevant literature; Section 2.3 describes the data employed in the analysis; Section 2.4 illustrates the empirical framework and the estimation strategy; Sections 2.5 and 2.6 present and comment the results; Section 2.7 concludes with a discussion of policy implications and recommendations.

## 2.2 Related literature

The empirical literature aimed at investigating the role of (automation) technology, globalisation and institutions in affecting labour market outcomes constitutes a large and growing body of research. Since the seminal work by Griliches (1969) on capital-skill complementarity, many scholars have examined the potentially biased effects of technology on the demand for, the productivity of, and consequently the wages of well-educated workers. In particular, the evidence in the early nineties provided by Katz and Murphy (1992) and Bound and Johnson (1992) gave a new momentum to considering the efficacy of the skill-biased technical change hypothesis in explaining the observed rising trend in wage inequality across countries and within groups (for exaustive surveys on this subject, see Chusseau *et al.*, 2008; Acemoglu and Autor, 2011).

More recently, an alternative to the skill-biased technical change hypothesis has been proposed that attempts to provide an explanation more suitable for the recent observation of declining relative demand and wages of middle-skilled workers – the so-called job polarisation phenomenon – in developed countries in particular (e.g., Autor *et al.*, 2003; Goos *et al.*, 2009; Acemoglu and Autor, 2011). The routine-biased technical change hypothesis (Autor *et al.*, 2003) argues that recent technological change, including artificial intelligence, robots and ICT developments more generally, allows for the replacement of workers doing routine tasks, which are often tasks undertaken by middle-skilled workers.

Among the proxies for automation technologies employed in the empirical literature as fundamental drivers of changes in employment, in the skill composition of labour demand and in wages, the focus has mostly been placed on computerisation, ICT, R&D expenditure and patents (e.g., Berman *et al.*, 1994; Morrison Paul and Siegel, 2001; Chennells and Van Reenen, 2002; Michaels *et al.*, 2014; Mann and Püttmann, 2018). Relying upon new data from the International Federation of Robotics (IFR) on industrial robots, progress has been achieved in the study of the impact of this contemporary automation wave on labour market outcomes, albeit with mixed results. Pioneering works in this field are Acemoglu and Restrepo (2020) and Graetz and Michaels (2018), who find evidence, respectively, of negative effects of robotics on wages and employment in the US and a positive influence on labour productivity growth in a panel of 17 countries. With specific reference to European economies, the findings are even less clear-cut. For instance, Chiacchio *et al.* (2018) point out a significant employment reduction as a result of increasing robot density (measured as the number of robots per thousand workers), an effect that is felt most strongly by middle-educated workers. By contrast, Dauth *et al.* (2018), analysing 402 German labour markets over the years 1994-2014, observe no effect of industrial robots on total employment, but adjustments in the composition of aggregate employment – specifically, job losses in manufacturing are offset by gains in the service sector. Similarly, by using data on employment from the European Labour Force Survey, Klenert *et al.* (2020) find that the adoption of an additional robot is associated, on average, with the employment of five additional workers.

Most of the technologies so far discussed, such as computerisation, ICT and robots are tangible in nature, but since the contribution of Corrado *et al.* (2005), a new emphasis has been placed on the incidence of so-called 'intangible' investments, previously not appropriately classified and counted by business and national accounts. As argued by Haskel and Westlake (2018), intangibles are characterised by unique economic properties, among which are their complementarity, especially with well-educated and high-paid workers, as well as their tendency to generate knowledge and/or idea spillovers among firms and their triggering of a "competitive process of investments in continuous product improvement". These features could help explain a variety of economic phenomena such as economic growth, secular stagnation, and rising income and wealth inequality (e.g., Corrado *et al.*, 2009; Glaeser, 2011; Bessen, 2016; Song *et al.*, 2019). In particular, relying on a panel of 10 developed countries and 30 industries over the period 1982-2005, Blanas *et al.* (2019) find that software, as a proxy for intangible technology, is associated with an increase in the demand for high-skilled workers only, while the tangible component of ICT has a positive impact on the demand for all workers types.

In addition to technological advances, the many dimensions of globalisation are thought to play an important role in affecting wage disparities (for recent reviews of the literature see, for instance, Kurokawa, 2014; Nolan *et al.*, 2019). According to the traditional Heckscher-Ohlin-Samuelson (HOS) model, trade openness is expected to benefit the abundant factor, which in developed countries would tend to suggest a rise in demand for, and therefore the return to, skilled relative to unskilled labour. In this respect, Wood (1995) analysed the labour-market effects of North-South trade, providing evidence of a significant impact of trade in reducing low-skilled employment in manufacturing in the North. Other studies have tended to provide confirmatory evidence of an effect of trade openness and/or liberalisation on the skill-premium in developed countries, although the effects tend to be smaller than those found for technology. For instance, Harrigan and Balaban (1999) observe that capital accumulation and the decline in traded goods prices increased the earnings of well-educated workers in the US, while Robbins (1996) and Beyer *et al.* (1999) highlighted a growth in the skill-premium in Chile. More recently, Michaels *et al.* (2014) and Epifani and Gancia (2008) find results suggesting a polarising and skill-biased effects of international trade, respectively. Goos *et al.* (2014) also find evidence to suggest that offshoring can lead to job polarisation.

In reconsidering the traditional HOS trade-based approach, which has attracted considerable criticism (e.g., Berman *et al.*, 1998; Goldberg and Pavcnik, 2007), attempts have been made to provide new explanations for the role played by different forms of trade engagement – in particular, international outsourcing and offshoring – in driving wage inequality worldwide (for a survey, see Hummels *et al.*, 2018). As argued by Feenstra and Hanson (1996), developing economies have played an increasing role in producing more skill-intensive inputs as a result of outsourcing by advanced economies, generating a rise in the relative demand for skilled workers and the skill-premium in both developed and developing countries. Conversely, Grossman and Rossi-Hansberg (2008) offer a different explanation: by assuming that the prices of goods remain unchanged, a cost decrease in offshoring produces an increase of unskilled activities offshored to developing countries. This, in turn, causes a rise in profits and sector expansion for those industries that heavily employ unskilled labour, pushing up its demand, productivity and wage, while leaving that of skilled labour unchanged. Therefore, through this channel, the skill-premium decreases. Glass and Saggi (2001) argue that outsourcing produces two offsetting effects. Outsourcing from developed to developing countries provides firms in developed countries with access to low-wage labour in the South. On the one hand, this increases competition for low-skilled labour in developed countries, reducing demand for low-skilled labour in developed countries. On the other hand, access to low-skilled and low-wage labour in developing countries increases profits for firms in developed countries, which can create incentives for innovation, and which ultimately can offset the negative effects of outsourcing on low-skilled labour in developed countries.

The evolution of the new patterns of globalisation has been embodied by Gereffi and Korzeniewicz (1994) in the concept of GVCs. According to Amador and Di Mauro (2015), GVCs describe "the full range of activities undertaken to bring a product or service from its conception to its end use and how these activities are distributed over geographic space and across international borders". The role of geographically dispersed production stimulated many studies to assess the impact of GVC participation on earnings and wages (e.g., Baumgarten *et al.*, 2013; Hummels *et al.*, 2014; Parteka and Wolszczak-Derlacz, 2015), although little has been done to quantify the effects of GVC participation on inequality. For instance, Lopez Gonzales *et al.* (2015) measure backward GVCs participation using the foreign value added share of a country's gross exports and find that increased GVC participation is associated with a narrowing wage gap between skilled and unskilled labour in both developed and emerging economies – a finding in line with the theoretical predictions by Grossman and Rossi-Hansberg (2008).

Overall, Helpman (2016) states that globalisation has contributed to the dynamics of relative wages and inequality, but only to a modest extent if evaluated against other factors. Among these other factors, a prominent position pertains to labour market institutions (for a survey of studies on the effects of labour market institutions on living standards, productivity and social cohesion, see Betcherman, 2012), such as measures of employment protection legislation (EPL). Existing contributions find mixed evidence on the effect of labour market protection on labour market outcomes. A number of studies have demonstrated a significant and substantial effect of strong labour market protections in mitigating wage differentials, as shown, for example, by Koeniger *et al.* (2007) for a sample of 11 OECD countries over the period 1973-1998. Conversely, using data for a sample of 20 OECD countries spanning the years 1973-2011 and indicators for regular and temporary contracts, Sparrman and Rossvoll (2015) find that the two indicators of labour market restrictions have opposite impacts on wage inequality, with EPL for temporary contracts shrinking the wage gaps and EPL for regular contracts intensifying them.

## 2.3 Data and descriptive statistics

The empirical analysis relies on annual panel data for 18 mostly developed European economies and 6 industries spanning the period 2008-2017.[1] The countries included in the sample are: Austria, Belgium, Czech Republic, Denmark, Germany, Estonia, Finland, France, Greece, Italy, Lithuania, Netherlands, Spain, Sweden, Slovenia, Slovak Republic, the United Kingdom and Japan.[2] Industries are classi-

[1] The set of countries, industries and time periods included in the analysis are dictated by data availability.

[2] Due to data constraints, we include as many countries as possible in the analysis. Removing Japan from the sample does not alter the main outcomes of the study, which are available upon request.

fied according to the one-digit-level NACE Rev. 2 (ISIC Rev. 4) codes and reported in Table 2.1.

**Table 2.1:** List of Sectors

| NACE code | Industry Description |
|---|---|
| A | Agriculture, forestry and fishing |
| B | Mining and quarrying |
| C | Total Manufacturing |
| D-E | Electricity, gas, steam; water supply, sewerage, waste management |
| F | Construction |
| P | Education |

*Source*: EU KLEMS (2019). Industry codes are NACE Rev. 2 (ISIC Rev. 4).

Data are collected and integrated from various sources. The main dataset is the EU KLEMS (2019) database, which provides information on skill composition, employment, labour compensation, hours worked, real fixed capital assets and value added by country-industry-year. The EU KLEMS dataset combines information on the shares of labour compensation and hours worked for three different workers types, which are distinguished on the basis of their educational attainment: university graduates; secondary and post-secondary education; and primary and lower secondary education.[3] Such a decomposition allows a multifaceted investigation of the dynamics of skill-premia, analysing whether workers are affected differently by tangible and intangible technologies, as well as by globalisation and labour market regulations. Relative wages are calculated as the ratio of the higher to the lower educated hourly wage, along the three dimensions (i.e., high- to medium-skilled workers, high- to medium-skilled workers and medium- to low-skilled workers). For instance, the skill-premium between high-skilled and middle-skilled workers

[3] Although the EU KLEMS (2019) data are mostly available at the two-digit level and from 1995 onwards, information on labour inputs only cover the period 2008-2017 and are provided according to the ISCED (2011) classification and NACE Rev. 2 (ISIC Rev. 4) one-digit industries. Throughout the analysis we refer to high-skilled as workers with a university degree; medium-skilled as workers who obtained upper secondary or post-secondary education, but not tertiary education; low-skilled as workers with primary and lower secondary education. Whenever the terms "less-skilled" or "lower-skilled" are used, we refer to medium- and low-skilled workers as an aggregate.

(SP HS/MS) is obtained as follows:

$$SP\frac{HS}{MS} = \frac{w_{hs}}{w_{ms}} = \frac{(\frac{\omega_{hs}LAB}{H_{hs}})}{(\frac{\omega_{ms}LAB}{H_{ms}})}$$

where $w_{hs}$ and $w_{ms}$ represent the hourly wages of high- and medium-skilled workers respectively, $\omega_{hs}LAB$ and $\omega_{ms}LAB$ indicate the total labour compensation of high- and medium-skilled workers, respectively, and $H_{hs}$ and $H_{ms}$ are the total hours worked by high- and medium-skilled workers, respectively. The ratios of high- to low-skilled ($SP\ HS/LS$) and medium- to low-skilled ($SP\ MS/LS$) wages are computed analogously. Relative skill supplies (i.e., the quantity effect) are measured by the ratios of hours worked in each analysed category – namely, the ratio of high-skilled hours worked to medium-skilled hours worked ($H/M$), the ratio of high-skilled hours worked to low-skilled hours worked ($H/L$), and the ratio of medium-skilled hours worked to low-skilled hours worked ($M/L$). The inclusion of relative skill supplies in the models is aimed at assessing whether there is a negative association between relative supply and the wage premia, as suggested by Katz and Murphy (1992), Card and Lemieux (2001) and Glitz and Wissmann (2017), amongst others.

As for capital inputs, based on Haskel and Westlake (2018), the EU KLEMS database groups asset types into tangibles and intangibles. Specifically, the tangible category includes ICT net of Software & Databases (i.e., hardware) and non-ICT (comprising, among others, transport equipment and total non-residential investments) capital stocks. The intangible assets contain Software & Databases (S&DB) and R&D capital stocks.[4] Following Michaels *et al.* (2014) and Blanas *et al.* (2019), all capital intensity variables are taken as a ratio to real gross value added. In this context, the crucial empirical questions, according to Haskel and Westlake (2018), are whether intangibles may produce either skill-biased or polarising effects and whether the tangible component of ICT, by contrast, may negatively affect wage dispersion (e.g., Acemoglu and Restrepo, 2020, 2018a).

The second source of data is the International Federation of Robotics (IFR) for

[4] For details, see Stehrer *et al.* (2019).

the stock of industrial robots by country-industry-year. According to the ISO 8373 definition, an industrial robot is "an automatically, reprogrammable, multipurpose manipulator programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications" (IFR, 2019). IFR data are broken down by industrial branches and classified according to ISIC Rev. 4, which makes them highly compatible with EU KLEMS. Nonetheless, due to limitations in the number of industries covered, the merger with EU KLEMS is possible only for the sectors reported in Table 2.1. The database contains information on the estimated operational stock of industrial robots and deliveries of robots for each country-industry-year. The operational stock of robots is constructed by assuming that robots operate for 12 years, on average, without losing economic value and leaving service precisely after the 12th year. Graetz and Michaels (2018) and Artuc *et al.* (2018), *inter alia*, argue that the assumption of no capital depreciation may be unrealistic. Therefore, the series of operational stock of robots is computed by applying the perpetual inventory method on robot deliveries to each country, industry and year in the sample, assuming a depreciation rate of 10%.[5] The robot density variable ($ROB$) is computed as robot stocks per million hours worked, rather than numbers of person engaged, on the grounds that workers in different countries/industries may vary in the quantity of hours worked (Graetz and Michaels, 2018). As observed by Blanas *et al.* (2019) and Jungmittag *et al.* (2019), robots are widely deployed in heavy industries, as a form of automation that links machineries (non-ICT capital) and software. Nonetheless, because of its tangible nature, the inclusion of robot density in the analysis is aimed at isolating potential independent effects on the skill-premia. Following Graetz and Michaels (2018), the inclusion of robot density in the model, as a distinct proxy for tangible technology, has the objective to test the skill-biased technical change hypothesis. In the second stage of our analysis we examine the role played by globalisation, and in particular trade openness and participation in GVCs, in strengthening

[5] As in Graetz and Michaels (2018) and Artuc *et al.* (2018), the constructed series is initialised using the IFR measure of operational stock of robots for the first year (2008), for each country and industry in the sample. Nonetheless, the two series exhibit a correlation coefficient of about 0.99, by making the results of the analysis qualitatively similar. These are not reported for reasons of space, but available upon request.

or mitigating the wage premia. For this purpose, we use data from the World Input-Output Database (WIOD) by Timmer *et al.* (2015) to measure the extent of trade openness at the country-industry level.[6] By aggregating information at the one-digit level, the overall measure of international trade ($GLOB$) is calculated as the sum of intermediate imports and total (i.e., intermediate plus final) exports expressed as a share of real gross value added. According to Epifani and Gancia (2008) and Michaels *et al.* (2014), we would expect either skill-biased or polarising effects of trade openness. Thus, whether $GLOB$ affects the skill-premia positively or negatively, for the three dimensions of wage inequality, is an empirical question.

OECD represents an additional source of data to account for participation in GVCs. Specifically, we rely on the Trade in Value Added (TiVA) database,[7] collecting information on domestic value added embodied in foreign final demand ($FFD\_DVA$) and foreign value added embodied in domestic final demand ($DFD\_FVA$). These two indicators can be interpreted, respectively, as "exports of value-added" and "imports of value added" – capturing upstream and downstream participation in GVCs, respectively – and are expressed as a share of real gross value added. The inclusion of participation in GVCs variables, in the second stage of the analysis, has the goal of detecting whether and how a different form of engagement in trade produces skill-biased effects along the two channels of imports and exports of value added. In a recent contribution, Wang *et al.* (2018) develop a model suggesting that downstream participation in GVCs is associated with higher wage inequality. In their model, GVC participation is associated with higher profitability, which in turn leads to demands for higher wages (based upon a fair wage assumption). Given the higher bargaining power of skilled workers, the model suggests that GVC participation increases the skill-premium. Franssen (2015) finds some evidence using WIOD data that upstream GVC participation is also associated with a higher skill-premium.

From OECD we also employ data on Employment Protection Legislation (EPL) in the third stage of the study, where the impact of labour market institutions on the skill-premia is assessed. Borrowing from IMF (2016) and Hantzsche *et al.*

[6] These data are available up to 2014.
[7] The 2018 OECD update of the TiVA database encompasses the years 2005 to 2015.

(2018), we construct two sector-specific measures of EPL for permanent and temporary workers.[8] In particular, the country-level EPL indicators are multiplied by the shares of permanent and temporary workers for each country-industry-year. For instance, the EPL index for permanent workers ($EPL\_PERM$) in country $c$, industry $i$ and year $t$ is computed according to the following formula:

$$EPL_{cit}^{Perm} = \left( \frac{E_{cit}^{Perm}}{E_{cit}^{Temp} + E_{cit}^{Perm}} \right) EPL_{ct}^{Perm} \tag{2.1}$$

where $E_{cit}^{Temp}$ and $E_{cit}^{Perm}$ represent temporary and permanent employees in country $c$, industry $i$ and year $t$, respectively, provided by Eurostat Labour Force Survey (EU-LFS).[9] The sector-specific EPL indicator for temporary workers ($EPL\_TEMP$), $EPL_{cit}^{Temp}$, is calculated analogously to equation (2.1), multiplying the share of temporary employees by $EPL_{ct}^{Temp}$. By including the sector-specific measures for EPL in the models, we test the hypothesis that the recent findings of a negative relationship between EPL and skill-premia (e.g., Koeniger *et al.*, 2007) are confirmed when the extent of labour market regulations are proxied by two separate, sector-specific indicators, one for each group of workers.

Real price variables are expressed in PPP adjusted 2005 international dollars, with the PPP conversion factors from Inklaar and Timmer (2014). The benchmark sample consists of 955 observations. Summary statistics, by country and industry, for the levels of the variables included in the empirical analysis are reported in Tables B.1a-B.1b and B.2a-B.2b of the Appendix, respectively.

In Figures 2.1 and 2.2 we document the evolution of the capital-intensity technologies (ICT (net of S&DB), S&DB and R&D), the skill-premia (*SP HS/MS*; *SP HS/MS*; *SP MS/LS*), the non-ICT capital intensity and robot density ($ROB$) from 2008 to 2017. To maintain the relative importance of the industries across time within each country, all the averages are calculated by first computing the within-

[8] The time period covered by EPL indicators ends in 2014. By assuming that labour market institutions are only slowly time varying, observations from 2015 to 2017 of EPLs are forecasted to gain useful information in the sample. Specifically, we employ uniformly weighted moving average using 4 lagged terms, 5 forward terms and the current observation in the filter.

[9] Missing observations in the series of temporary employees are filled through linear interpolation.

country means across all sectors, weighted by the 2008 share of each industry's employment, and then subsequently using the unweighted averages across countries. Such an approach means that observed developments in the skill-premia do not reflect wage developments due to a changing composition of economic activity over time.

Panel (a) of Figure 2.1 shows the patterns of the capital-intensity technologies. By including R&D among the intangible capital stocks, the new EU KLEMS (2019) database release allows us to expand and update some of the previous descriptive findings in the literature (e.g., Blanas *et al.*, 2019), albeit for a smaller number of industries. In particular, the important contribution of R&D capital stock can be observed, with its share increasing from 10% in 2008, to almost 14% in 2017. The shares of ICT (net of S&DB) and S&DB exhibit more modest growth over the same period: from 4.5% to 5.5% for ICT and from 2.2% to about 2.9% for S&DB. Although ICT and S&DB constitute lower shares compared to the R&D capital intensity, we must emphasise the fact that the investments in these specific assets grew by about 30% over the ten years under investigation.

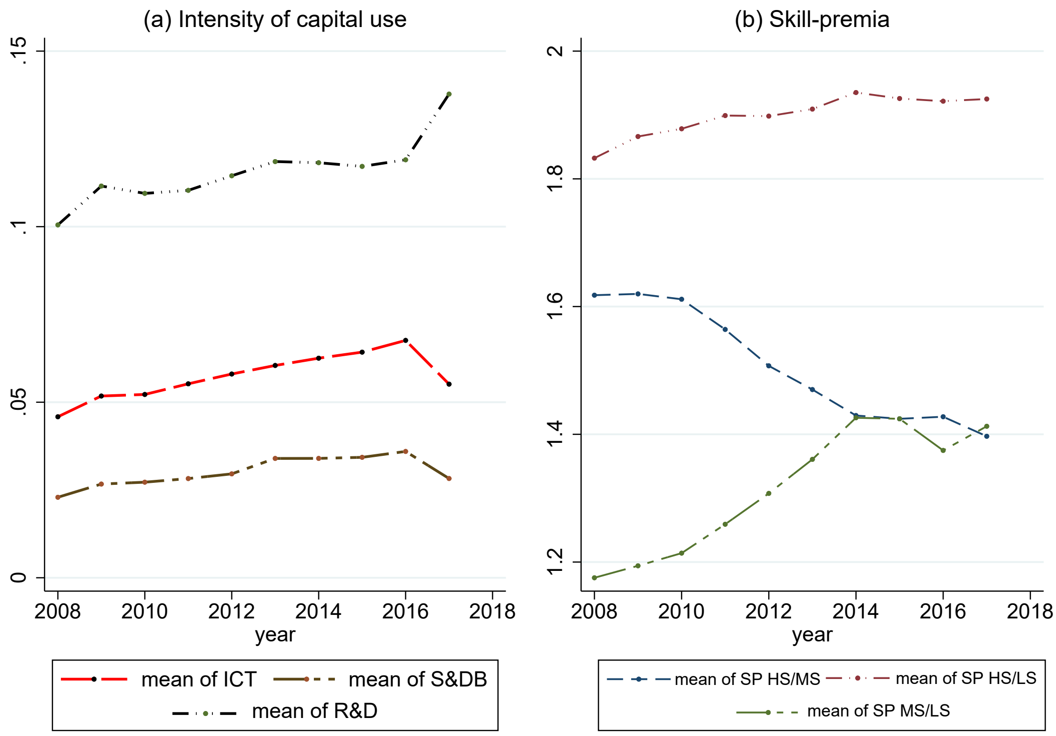
Panel (b) of Figure 2.1 reports the skill-premia evolution. The wage premium between high- and low-skilled workers ($SP\ HS/LS$) increased somewhat over the period, while the wage gap between high- and medium-skilled workers ($SP\ HS/MS$) showed a more marked decline.[10] Conversely, the increase in the wage dispersion between medium- and low-skilled workers ($SP\ MS/LS$) appears in line with the recent findings of European Union (2019, 2015).

With respect to the behaviour of wage dispersion within countries during the analysed period,[11] it can be noticed that although the vast majority of countries experienced a slight decline in the skill-premium between high- and medium-skilled workers, Finland, Spain and Slovenia showed a rising trend. As for the wage gap between high- and low-skilled workers, a stagnant evolution prevailed. Ultimately, the growth trend in the skill-premium between medium- and low-skilled labour, as shown in the Panel (b) of Figure 2.1, was mainly driven by

[10] Similarly, IMF (2017) documents a stagnating or shrinking wage-dispersion in European economies from 2006 to 2014.

[11] Graphs representing the evolution of wage-gaps for a subsample of European economies are reported in Figures B.1-B.3 in the Appendix to this paper.

Figure 2.1: Developments in the Intensity of Technology Use and the Skill Premia



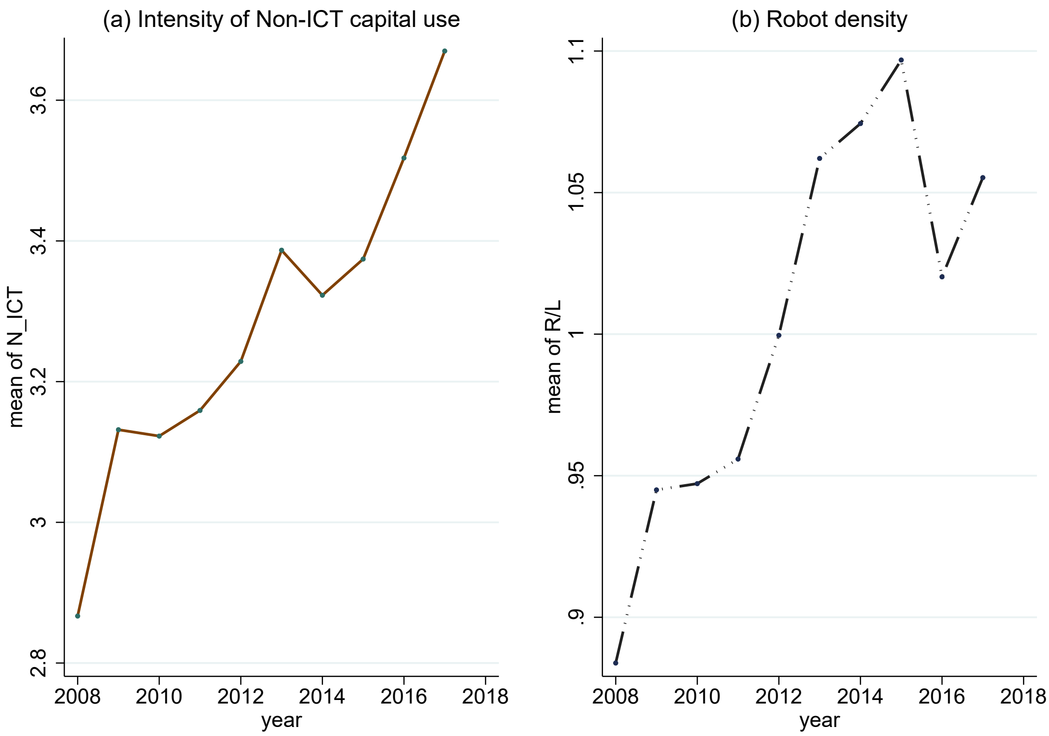

*Sources*: Authors' calculation based on EU KLEMS (2019).

Austria, Germany and Slovenia.

Developments in the intensity of use of non-ICT capital and robot density ($ROB$) show strong rising trends, as illustrated in Figure 2.2. In Panel (a) of Figure 2.2, the evolution of non-ICT capital intensity ($N\_ICT$) seems to extend the descriptive evidence by Blanas *et al.* (2019), which highlights an increase of "Traditional Capital" starting from the 2000s after nearly 20 years of unpredictable patterns.[12] Likewise, in Panel (b) of Figure 2.2, robot density – computed as the stock of industrial robots per million hours worked – followed a clear path of growth

[12]As argued by Blanas *et al.* (2019), data on intangible investments, especially software, were not fully captured in earlier EU KLEMS versions, being potentially included in both ICT and non-ICT capital assets. In confirmation of this, McGrattan (2020) provides evidence of a high correlation between investments in non-ICT capital and intangible assets.

Figure 2.2: Developments in the Intensity of Non-ICT capital Use and Robot Density




*Sources*: Authors' calculations based on EU KLEMS (2019) and IFR (2019).

(albeit with a short-run slowdown between 2015 and 2016), fuelling concerns about the future of human work (e.g., Frey and Osborne, 2017; Berg *et al.*, 2018). Overall, both non-ICT capital and robot density recorded an increase of about 20% during the period 2008-2017.

## 2.4 Empirical models and estimation strategy

Relying on the theoretical contributions described in section 2.2 and empirical works, amongst others, of Goldin and Katz (2009), Michaels *et al.* (2014), Glitz and Wissmann (2017), Graetz and Michaels (2018) and Blanas *et al.* (2019), the estimated system of three equations accounting for the evolution of skill-premia can be expressed as follows:

$$\begin{cases} \ln\left(\dfrac{w_{hs}}{w_{ms}}\right)_{cit} = \alpha_{1,c} + \beta_{1,i} + \gamma_{1,r} + \delta_{1,r}\ln(ROB)_{cit} + \delta_{1,k}K^{'}_{cit} \\ \qquad + \delta_{1,y}\ln Y_{cit} + \delta_{hm}\ln\left(\dfrac{H}{M}\right)_{cit} + \epsilon_{1,cit} \\ \ln\left(\dfrac{w_{hs}}{w_{ls}}\right)_{cit} = \alpha_{2,c} + \beta_{2,i} + \gamma_{2,r} + \delta_{2,r}\ln(ROB)_{cit} + \delta_{2,k}K^{'}_{cit} \\ \qquad + \delta_{2,y}\ln Y_{cit} + \delta_{hl}\ln\left(\dfrac{H}{L}\right)_{cit} + \epsilon_{2,cit} \\ \ln\left(\dfrac{w_{ms}}{w_{ls}}\right)_{cit} = \alpha_{3,c} + \beta_{3,i} + \gamma_{3,r} + \delta_{3,r}\ln(ROB)_{cit} + \delta_{3,k}K^{'}_{cit} \\ \qquad + \delta_{3,y}\ln Y_{cit} + \delta_{ml}\ln\left(\dfrac{M}{L}\right)_{cit} + \epsilon_{3,cit} \end{cases} \tag{2.2}$$

where $c = 1,\dots,C$, $i = 1,\dots,I$ and $t = 1,\dots,T$ indicate, respectively, country, industry and time. The dependent variables are the logarithms of the skill-premium between high and middle-skilled workers ($SP\ HS/MS$), high and low-skilled workers ($SP\ HS/LS$) and medium and low-skilled workers ($SP\ MS/LS$), respectively; $\alpha_{j,c}$, $\beta_{j,i}$ and $\delta_{j,t}$ (with $j = 1,2,3$) are country, industry and time fixed-effects, respectively, to control for cross-country and cross-industry unobserved heterogeneity, and to capture time varying unobserved factors, such as global shocks; $\ln(ROB)$ is the logarithm of robot density;[13] $K^{'}$ is a vector of EU KLEMS capital intensity variables[14] – the shares of real fixed $ICT$ (net of S& DB), $R\&D$, $N\_ICT$ and $S\&DB$

[13]To deal with the zero values in the series of stock of robots, which are reflected in the absence of robot density, we make use of the inverse hyperbolic sine transformation (see, for instance, Burbidge *et al.*, 1988; Pence, 2006; Bellemare and Wichman, 2020), defined as $\ln\left(x_{cit} + \left(x_{cit}^2 + 1\right)^{1/2}\right)$. Similarly as in Artuc *et al.* (2018), estimations are also carried out using $\ln(1 + x_{cit})$. The results are qualitatively comparable and available upon request.

[14]Following Michaels *et al.* (2014) and Blanas *et al.* (2019), the EU KLEMS share variables are expressed in levels rather than logarithms, due to the near-zero values for some country-industry pairs in our sample: this, in turn, implies large negative values after the logarithmic transformation. The use of log-transformation, rather than levels, for the robot density variable is dictated by the heavy right-skewness distribution and nonlinearities affecting the non-transformed variable. Additionally, as robustness checks, we lagged by one year the main independent variables to attenuate potential simultaneity bias: the estimations of this alternative model specification do not alter the core results of the analysis, which are available upon request.

capital stocks to real gross value added; $\ln Y$ is the logarithm of real gross value added, included as control for industry-scale effects; $\ln\left(\frac{H}{M}\right)$, $\ln\left(\frac{H}{L}\right)$ and $\ln\left(\frac{M}{L}\right)$ stand for, respectively, the relative supplies of high- to medium, high- to low and medium- to low-skilled workers; and $\epsilon_j$ are well behaved error terms (with $j = 1,2,3$).

The three skill-premium equations in (2.2) are simultaneously estimated using Seemingly Unrelated Regressions (SUR) techniques (Zellner, 1962) to control for potential correlation of the error terms across the equations. According to Goldin and Katz (2009) and Glitz and Wissmann (2017), identification of the system given by equation (2.2) relies on the assumption that the relative skill supplies are inelastic in the short-run (i.e., predetermined), stemming from past investment decisions in education and training. Therefore, under such an assumption, the wage premia and relative skill supplies are not jointly determined.

## 2.5 Basic results and discussion

This section presents and discusses the estimates for the first stage of the study, where the focus is placed upon the role played by tangible and intangible technologies.

Table 2.2 reports the SUR results for the three wage premium equations described in the previous section: high- to medium-skilled workers ($SP\ HS/MS$), in Column (1); high- to low-skilled workers ($SP\ HS/LS$), in Column (2); medium- to low-skilled workers ($SP\ MS/LS$), in Column (3). The Breusch-Pagan test strongly rejects the null hypothesis of contemporaneously independent disturbances across the equations – providing support for the adoption of SUR estimates. In terms of our control variables, we find evidence of the negative impact of relative skills supplies on wage premia for all the estimated models, in line, among others, with Krusell *et al.* (2000) and Goldin and Katz (2009). Consistent with some of the findings in Michaels *et al.* (2014), non-ICT capital displays complementarity with medium-skilled workers, as revealed by the negative and positive significant coefficients in columns (1) and (3) respectively.

Turning to our main variables of interest, estimated coefficients on the capital-skill complementarity effect for robot density (our first measure of tangible technologies) are in line with our expectations and suggest that they widen the skill-premia of high-skilled with respect to both medium- and low-skilled workers (see columns (1) and (2)), results in line with those of Graetz and Michaels (2018). Such results may reflect a complementary relationship between robot density and high-skilled workers or a substitution effect with respect to low- and medium-skilled workers. In elasticity terms, all else being equal, a one percent increase in robot density is associated, on average, with a growing wage gap by 0.025 and 0.037 percent, respectively, for high- to medium skilled labour and high- to low-skilled labour.

Likewise, the intangible part of ICT – i.e., $S\&DB$ – seems to severely disadvantage less-skilled labour in terms of wage dispersion. In this case, *ceteris paribus*, a one percentage point increase in the intensity of $S\&DB$ use is associated, on average, with an increase in the skill-premium between high- to low-skilled workers, high- to low-skilled and medium- to low-skilled workers, of around 0.6, 0.8 and 0.25 percent respectively. On the contrary, the tangible component of the $ICT$ (net of S&DB) capital – i.e., hardware – appears to improve, in particular, the wages of middle-educated workers, relative to high- and low-skilled workers, as shown in columns (1) and (3). Results in Column (2) further suggest that ICT capital benefits low-skilled relative to high-skilled workers. Such results may be due to ICT (net of S&DB), as a General-Purpose Technology,[15] reaching maturity and its pervasiveness in advanced economies that has facilitated innovation dynamics in many industries as well as boosting the adaptability, productivity and wages of less-skilled labour (e.g., Aghion and Commander, 1999; Conceição and Galbraith, 2012; Acemoglu and Restrepo, 2020, 2018b).

With regard to the impact of the intensity of $R\&D$ expenditure, the second proxy for intangible technology, the estimates in columns (1) and (3) reflect and complement those reported by Michaels *et al.* (2014) and Breemersch *et al.* (2019), who observe polarising effects of $R\&D$ related process innovations that impact upon middle-skilled labour negatively. For this specific relationship, all else being equal, a one percentage-point increase in the $R\&D$ share is accompanied, on average, by an increase in the skill-premium between high- and medium skilled labour by 0.16 percent and a reduction in the skill-premium between medium- and low-skilled labour by 0.18 percent, respectively.

[15] See, for instance, Bresnahan and Trajtenberg (1995) and Helpman (1998).

**Table 2.2:** Regression Results of Relationship between Tangible and Intangible Investments and Relative Wages

| | (1) | (2) | (3) |
|---|---|---|---|
| Dep. Var: ln($SP$) | (HS/MS) | (HS/LS) | (MS/LS) |
| ln(ROB) | 0.025** | 0.037*** | 0.013 |
| | (0.013) | (0.011) | (0.013) |
| ICT | -0.978*** | -0.313** | 0.670*** |
| | (0.169) | (0.149) | (0.168) |
| R&D | 0.160*** | -0.021 | -0.182*** |
| | (0.045) | (0.039) | (0.044) |
| S&DB | 0.572*** | 0.829*** | 0.248*** |
| | (0.096) | (0.085) | (0.095) |
| N_ICT | -0.031*** | 0.005 | 0.036*** |
| | (0.005) | (0.004) | (0.005) |
| ln Y | -0.113*** | -0.003 | 0.108*** |
| | (0.021) | (0.018) | (0.021) |
| ln(H/M) | -0.034** | | |
| | (0.013) | | |
| ln(H/L) | | -0.026** | |
| | | (0.012) | |
| ln(M/L) | | | -0.039*** |
| | | | (0.013) |
| Obs | | 955 | |
| R-squared | 0.637 | 0.731 | 0.688 |
| Breusch-Pagan (chi-squared) | | 663.922 | |
| Year fixed-effects | Yes | Yes | Yes |
| Industry fixed-effects | Yes | Yes | Yes |
| Country fixed-effects | Yes | Yes | Yes |

*Notes*: Seemingly Unrelated Regressions (SUR), with small-sample adjustment for computing the covariance matrix for the equation residuals. All the estimates are weighted using 2008 sectoral employments weights to aggregate to the country level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

It is important to note that the incidence of the intensity of $S\&DB$ capital in exacerbating wage inequalities is economically more relevant than $R\&D$, although the share of $S\&DB$ in gross value added as well as its growth rate over the period under investigation are considerably lower. The effect of $S\&DB$ on the skill-premium between high- and medium-skilled labour, for example, is about 3.5 times as large as the effect of an increase in $R\&D$. Such an outcome highlights that intangibles are of great importance in driving the dynamics of wage differentials. In this respect, our estimates reveal that $S\&DB$, as a proxy for digitalisation technology, has the potential to boost inequalities to a greater extent than $R\&D$ or robot investment (e.g., Balsmeier and Woerter, 2019; Arntz *et al.*, 2020).

Overall, our findings suggest that disentangling the roles played by different kinds of technological advances in a systematic and comprehensive analytical framework, can favour a better understanding of the dynamics of wage dispersion within the labour market induced by tangible and intangible automation technologies.

## 2.6 Robustness and extensions

In this section we consider extensions to the baseline analysis described above. Specifically, the first extension, reported in sub-section 2.6.1, involves the inclusion of variables capturing globalisation in our analysis, while sub-section 2.6.2 further includes sector-specific proxies for labour market regulations. Through this analysis we are interested in both the effects of these sets of variables on the skill-premia and their impacts on the relationships between technologies and the skill-premia described in the previous section.

### 2.6.1 Globalisation

In the second stage of our investigation, the supplemental role played by different forms of trade engagement in determining the dynamics of the skill-premia is taken into consideration. Trade is supposed to produce effects on wage dispersion through the relative prices of skilled-intensive and unskilled-intensive goods (e.g., Wood, 1995). For this purpose, we augment the models proposed in Section 2.4 by including two alternative indexes of globalisation: 1) an overall measure of trade openness ($GLOB$), calculated as the ratio of imports plus exports to real gross value added, and 2) indicators of upstream ($DFD\_FVA$) and downstream

($FFD\_DVA$) GVCs participation. Results from including these indicators alongside the technology variables are reported in Table 2.3.

The extended regressions show that the main findings uncovered in the previous section are generally robust to the inclusion of further control variables – with the only exceptions of $ICT$ (net of S&DB) in columns (2) and (5), which remain negative but are no longer significant, and robot density ($ROB$) in column (4), which remains positive but is no longer significant.

Turning to the contribution of globalisation as an additional determinant of the skill-premia dynamics, the estimates suggest – similarly to Michaels *et al.* (2014) – that a higher trade openness ($GLOB$) produces polarising effects, with middle-skilled labour suffering relative to high- and low-skilled labour. This can be seen by the positive and significant coefficient on $GLOB$ in Column (1) and the negative and significant coefficient in Column (3). Specifically, *ceteris paribus*, a one percentage point increase in $GLOB$ is associated with an increase in the wage premium between high- and medium-skilled labour of about 0.05 percent, and to a reduction of the wage premium between medium- and low-skilled labour by about 0.07 percent, respectively. The results further suggest (Column 2) that trade openness produces a decline in the wage gap between high- and low-skilled workers, suggesting that trade openness is in general low-skill-biased for this specific relationship. This outcome is also in line with previous findings by Spilimbergo *et al.* (1999) and IMF (2002), who highlight a decline of the wage premium between skilled and unskilled workers in countries well-endowed with capital, as a result of a higher participation in trade. Furthermore, the modest incidence of trade openness on relative wages confirms the conclusions by Helpman (2016).

With respect to the effects provided by GVC participation, in columns (4) and (5) we find evidence of a negative association between downstream participation ($FFD\_DVA$) and the skill-premia involving high- to medium-skilled labour as well as high- to low-skilled labour. Such a finding is in line with the theory of Grossman and Rossi-Hansberg (2008), which suggests that an increase in offshoring of low-skilled tasks to developing countries raises wages for low-skilled labour and reduces the skill-premium.

The analysis carried out up to this point reveals that the international trade, together with technological advances, plays a crucial role in strengthening or

**Table 2.3:** Regression Results with Globalisation Variables

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dep. Var: ln($SP$) | (HS/MS) | (HS/LS) | (MS/LS) | (HS/MS) | (HS/LS) | (MS/LS) |
| ln(ROB) | 0.043*** | 0.028** | -0.013 | 0.010 | 0.028** | 0.021 |
| | (0.016) | (0.014) | (0.015) | (0.015) | (0.013) | (0.015) |
| ICT | -0.925*** | -0.289 | 0.641*** | -0.792*** | -0.225 | 0.563*** |
| | (0.209) | (0.186) | (0.203) | (0.199) | (0.173) | (0.197) |
| R&D | 0.205*** | -0.051 | -0.257*** | 0.167*** | -0.049 | -0.218*** |
| | (0.052) | (0.046) | (0.050) | (0.050) | (0.044) | (0.050) |
| S&DB | 0.611*** | 0.960*** | 0.340*** | 0.593*** | 0.881*** | 0.271** |
| | (0.118) | (0.105) | (0.114) | (0.108) | (0.095) | (0.107) |
| N_ICT | -0.035*** | 0.003 | 0.037*** | -0.034*** | 0.005 | 0.037*** |
| | (0.006) | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) |
| ln Y | -0.146*** | -0.002 | 0.142*** | -0.113*** | 0.022 | 0.127*** |
| | (0.024) | (0.021) | (0.024) | (0.026) | (0.022) | (0.026) |
| ln(H/M) | -0.036** | | | -0.036** | | |
| | (0.015) | | | (0.015) | | |
| ln(H/L) | | -0.030** | | | -0.026** | |
| | | (0.013) | | | (0.013) | |
| ln(M/L) | | | -0.043*** | | | -0.048*** |
| | | | (0.015) | | | (0.014) |
| GLOB | 0.048*** | -0.028*** | -0.075*** | | | |
| | (0.011) | (0.010) | (0.011) | | | |
| FFD_DVA | | | | -0.210** | -0.225*** | 0.017 |
| | | | | (0.095) | (0.085) | (0.096) |
| DFD_FVA | | | | -0.010 | 0.006 | 0.015 |
| | | | | (0.009) | (0.008) | (0.009) |
| Obs | | 703 | | | 801 | |
| R-squared | 0.646 | 0.724 | 0.688 | 0.634 | 0.726 | 0.678 |
| Breusch-Pagan (chi-squared) | | 487.744 | | | 543.750 | |
| Year fixed-effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry fixed-effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Country fixed-effects | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes*: Seemingly Unrelated Regressions (SUR), with small-sample adjustment for computing the covariance matrix for the equation residuals. All the estimates are weighted using 2008 sectoral employments weights to aggregate to the country level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

mitigating the wage differentials within the labour market. Additionally, by disaggregating wage premia along the three dimensions considered we are able to better identify potential "winners and losers" – in relative terms – from technology and globalisation. Results suggest that while openness in a general sense has both polarising and low-skill-biased effects, offshoring can diminish the skill-premia in line with existing theoretical results.

### 2.6.2 Labour Market Regulations

The last stage of our investigation deals with the impact of labour market institutions on wage dispersion, starting from the assumption that these are likely to be effective at attenuating inequalities especially in the European countries (e.g., Koeniger *et al.*, 2007).[16] To this end, we further augment the models with the sector-specific measures of EPL for permanent ($EPL\_PERM$) and temporary ($EPL\_TEMP$) employees described in Section 2.3. Table 2.4 reports the estimated results of the models that consider the roles of technologies, trade and labour market institutions as determinants of the dynamics of wage premia.

As for the main findings uncovered in Section 2.5 and sub-section 2.6.1, it can be noticed that once we control for the strictness of employment protection law, the coefficients associated with robot density become insignificant for all estimated models. Conversely, the coefficients on $ICT$ (net of S&DB) recover their statistical significance. Coefficients on the $R\&D$ are also now found to be sensitive to the choice of proxy for globalisation. Common to both model specifications, the contribution of $S\&DB$ turns out to be fully robust in affecting only the wage gaps between high- to medium-skilled and high- to low-skilled labour,[17] as indicated in columns (1)-(2) and (4)-(5). Such a specific finding corroborates the view of Haskel

[16]Since the sector-specific EPL indicators are constructed relying upon the shares of permanent and temporary employees, for which data are available only for European countries, Japan is excluded from the estimated sample.

[17]The increased size of the coefficients for the $S\&DB$ variables is due to a drop in the observations for some specific country-industry pairs in the sample, for which the sector-specific EPL measures cannot be constructed because of data availability for permanent and/or temporary employees. Specifically, the vast majority of missing observations occur for the "Mining and Quarrying" (B) and the "Electricity, gas, steam; water supply, sewerage, waste management" sectors. This, in turn, would suggest that the impact of $S\&DB$ is not as strong for these industries. The outcomes of the regressions performed on the reduced sample size obtained by excluding the EPL variables, as well as the magnitude of the $S\&DB$ coefficients, do not differ significantly from those reported in Table 2.4 - these are available upon request.

and Westlake (2018), according to which managing intangible technologies, such as $S\&DB$, entails the need for specific skills, education and training. As a result, a higher $S\&DB$ leads to a higher demand for high-skilled workers and in turn higher wages, which tends to exacerbate the wage premia.

Additionally, when controlling for the strictness of employment protection law, the coefficients associated with the relative supplies of skills ($H/M$, $H/L$ and $M/L$) become insignificant for all estimated models. In line with Acemoglu (2003), such a result can be explained on the grounds that European industries, due to the degree of compression in the wage structure over the business-cycle stemming (at least to some extent) from the strict labour market regulations, might be incentivised to adopt technologies that are low-skill-biased. The latter, subsequently, would push-up productivity and wages for medium- and low-skilled workers, as some of our findings seem to point to. This, in turn, implies limits placed on the skill upgrading of the workforce, de-emphasising the role of market forces through the channels of demand for and supply of skills (e.g., Bertola, 1999; Boeri *et al.*, 2012).

Although the evidence for the trade openness variables ($GLOB$) is confirmed in this further extension of the analysis, as shown in columns (1)-(3), one interestingly finding emerges regarding the impact of GVCs participation. In column (4) of Table 2.4 the coefficient for the upstream participation ($DFD\_FVA$) becomes positive and statistically significant, a result in line with those of Franssen (2015).

Ultimately, as expected, stricter employment protection rules, as proxied by the sector-specific EPL measures ($EPL\_PERM$ and $EPL\_TEMP$), have strongly negative effects on the skill-premia, for all the estimated models. In fact, *ceteris paribus*, a unit increase in $EPL\_PERM$ is accompanied, on average, by a reduction in the skil-premium of between 0.2 and 0.6 percent, with the effects tending to be largest for the high- to low-skilled wage premium. Similarly, all else equal, a unit increase in $EPL\_TEMP$ is associated, on average, to a narrowing of the skill-premium by between 0.3 and 0.9 percent, with the effects again being largest for the high- to low-skilled wage premium.

To sum up, the extended analysis reported in this section supports and reinforces the view that a systematic and comprehensive investigation of the core drivers of skill-premia requires a multifaceted approach. By breaking down technologies into tangible and intangible categories, and globalisation into trade open-

**Table 2.4:** Regression Results with Labour Market Regulations

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dep. Var: ln(SP) | (HS/MS) | (HS/LS) | (MS/LS) | (HS/MS) | (HS/LS) | (MS/LS) |
| ln(ROB) | -0.010 | -0.025 | -0.015 | -0.019 | -0.020 | -0.001 |
| | (0.017) | (0.016) | (0.016) | (0.016) | (0.015) | (0.016) |
| ICT | -1.264*** | -0.544** | 0.722*** | -1.154*** | -0.446** | 0.708*** |
| | (0.228) | (0.213) | (0.216) | (0.212) | (0.198) | (0.209) |
| R&D | 0.152*** | 0.045 | -0.108** | 0.065 | 0.028 | -0.038 |
| | (0.053) | (0.049) | (0.050) | (0.050) | (0.046) | (0.049) |
| S&DB | 2.335*** | 2.032*** | -0.312 | 2.028*** | 1.994*** | -0.048 |
| | (0.434) | (0.403) | (0.409) | (0.410) | (0.379) | (0.402) |
| N_ICT | -0.013** | -0.001 | 0.011** | -0.008 | 0.001 | 0.009* |
| | (0.006) | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) |
| ln Y | 0.094*** | 0.047* | -0.048* | 0.165*** | 0.073** | -0.093*** |
| | (0.029) | (0.028) | (0.028) | (0.031) | (0.029) | (0.031) |
| ln(H/M) | 0.014 | | | 0.011 | | |
| | (0.015) | | | (0.015) | | |
| ln(H/L) | | 0.013 | | | 0.009 | |
| | | (0.014) | | | (0.014) | |
| ln(M/L) | | | 0.011 | | | 0.004 |
| | | | (0.014) | | | (0.014) |
| GLOB | 0.032*** | -0.028*** | -0.060*** | | | |
| | (0.012) | (0.011) | (0.011) | | | |
| FFD_DVA | | | | -0.312*** | -0.307*** | 0.015 |
| | | | | (0.099) | (0.095) | (0.101) |
| DFD_FVA | | | | 0.043* | 0.011 | -0.032 |
| | | | | (0.023) | (0.021) | (0.022) |
| EPL_PERM | -0.003*** | -0.006*** | -0.002*** | -0.003*** | -0.005*** | -0.002*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| EPL_TEMP | -0.007*** | -0.009*** | -0.003* | -0.006*** | -0.008*** | -0.003** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Obs | | 555 | | | 637 | |
| R-squared | 0.684 | 0.769 | 0.703 | 0.677 | 0.767 | 0.693 |
| Breusch-Pagan (chi-squared) | | 415.484 | | | 471.520 | |
| Year fixed-effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry fixed-effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Country fixed-effects | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes*: Seemingly Unrelated Regressions (SUR), with small-sample adjustment for computing the covariance matrix for the equation residuals. All the estimates are weighted using 2008 sectoral employments weights to aggregate to the country level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

ness and GVC participation, the empirical evidence shows that both technology and globalisation are likely to produce different – and sometime offsetting – effects on the wage differential dynamics. Our findings point to a crucial role played by intangible technologies in either increasing the wage gap or producing polarising effects, as in the case of $S\&DB$ and $R\&D$, respectively. As for the impact of tangible technologies, the skill-biased effect of robots turns out to be not fully robust, especially when the contribution of labour market institutions is taken into consideration – such a result appears to be in line with the mixed empirical evidence so far available for the European economies (Reiter, 2019). On the contrary, $ICT$ (net of S&DB) proves to be associated with a lower high-skill premium, in particular for the high- to middle-skilled premium.

Turning to the effects of globalisation on the skill-premia, the overall indicator of trade openness mainly identifies patterns of polarisation, widening wages inequality at the expense of middle-skilled workers. By contrast, downstream GVC participation narrows the skill-premia in favour of less-skilled labour, whereas there is some limited evidence to suggest that upstream GVC participation worsens the wage differential between high- and medium-skilled workers.

## 2.7 Conclusions

The growing concerns about the issues of artificial intelligence, robotics, automation and digital innovation on the future of people's working lives, supplemented by the well-known puzzling influence of global trade and offshoring, has recently led many researchers to question and investigate the real effectiveness and magnitude of the impact exerted by these powerful economic forces within the labour market, especially in developed countries. The results of several studies have strengthened such concerns, leading to call for policies directed at protecting jobs and industries from new and/or foreign threats. By contrast, other scholars reject such a pessimistic view, claiming that many of the fears would be clearly unfounded.

In this paper, we contribute to the ongoing debate by studying the effects of automation technologies, as well as different forms of international trade engagement and labour market institutions, on the wage premia, relying on the skill-biased technical change and polarisation approaches. The empirical analysis is performed using annual data for a panel of 18 mostly advanced European economies and 6 industries over the period 2008-2017. According to the recent literature, new technologies are split into tangibles and intangibles, and globalisation into trade openness and GVCs participation, while the impact of labour market institutions on wage disparities is evaluated by making use of sector-specific measures of EPL for permanent and temporary employees. In order to detect potential specific effects of the main determinants of wage gaps for different workers types, we break down the relative wages in three categories (high- to medium-skilled, high- to low-skilled and medium- to low-skilled labour) and simultaneously estimate a system of equations employing SUR techniques to take into account correlation of the error terms across equations.

The core results of our analysis can be summarised as follows. First, intangible technologies, as proxied by Software & Databases and R&D capital intensity, produce skill-biased and polarising effects, respectively. Second, we find only weak evidence of the skill-biased impact of robotisation. Third, the role of globalisation on the dynamics of the wage differentials depends upon the specific measure considered – whether trade openness or GVCs participation. Higher trade openness is mainly associated with a polarisation of the wage distribution, while downstream GVC participation favours lower-skilled labour and upstream participation benefits high-skilled workers. Finally, employment protection rules prove to be effective in mitigating wage differentials.

From a policy perspective, the main challenge is represented by the effects of intangible technologies. As our findings suggest, the strong complementarity between high-skilled workers and S&DB as well as the job polarisation of R&D related innovations call for policymakers to invest in education and skills training for less-skilled workers, particularly given that intangible technologies are likely to pervade the workplace even more in the future. Additionally, the weak evidence of a skill-biased impact of robotisation should not be underestimated, as the speed of deployment of new and qualitatively improved robots is predicted to rise dramatically in the coming years. Overall, policymakers will need to play a crucial role in ensuring that the economic benefits stemming from new technologies will not be focussed on a small elite and further research should be devoted to understanding the exact mechanisms by which rising automation might lead to new job opportunities or destruction.

Furthermore, our findings point to “hollowing-out” effects of trade openness upon middle-skilled labour. Blanchard and Willmann (2016) suggest that subsidising human capital investments and/or providing temporary wage top-ups for this particular category of workers may be a relevant policy. Conversely, the results on our GVC indicators suggest that an open trade policy, with offshoring low-skilled activities being encouraged, can actually help reduce skill-premia, although further work looking at the employment level effects of offshoring would be useful.

In essence, our investigation suggests that the influence of automation, tangible and intangible technologies, and international trade can either be positive or negative in affecting the dynamics of the skill-premia, with the effects depending on the specific dimensions, characteristics and economic mechanisms underlying them. Such a conclusion implies that there may exist a third way, which lies between the technological optimists and pessimists, whereby the different dimensions of technology (and globalisation) affect workers in varied ways.

CHAPTER 3

# ROBOTIC CAPITAL-SKILL COMPLEMENTARITY


## Abstract

The rise of artificial intelligence and automation is fuelling anxiety about the replacement of workers with robots, computers and digital technologies. Such an increasing use of automatised routines and robots in production process throughout nearly all sectors of the economy has spurred a sharper focus on the labour market implications. In this paper, we investigate the existence of complementarity/substitutability across several forms of capital with respect to three skill types: high-, medium- and low-skilled workers. Relying upon a constructed measure of robotic capital, we test the robotic capital-skill complementarity hypothesis on two samples of countries and industries, based on WIOD and EU KLEMS datasets. By making use of different frameworks, our results point to a lower elasticity of substitution between robotic capital and skilled labour. Furthermore, we find evidence of polarising effects produced by robotic and ICT capital equipment. The results turn out to be robust to different computations of robotic capital, as well as workers grouping.



**Keywords**: Automation, Robotisation, Wage Inequality, Technology, ICT, Polarisation

**JEL Classification**: C23, E24, J31, O33, O47

## 3.1 Introduction

The spread of robotisation and, more generally, of automation is seen as one of the most challenging issues for the future of workers and their integration into society and economy of our communities (e.g., Ford, 2015; West, 2018; Susskind, 2020).

Among the major questions, the risk of disappearing of the middle-class and the increasing level of between-group inequality, as a result of a more intensive use of new technologies, has spurred an intense debate. As proof of this, Jaimovich *et al.* (2020) find that the likelihood of working in routine occupations between the pre-polarisation era and the post-polarisation one decreased roughly by 16%. Further causes of concern are linked to the ongoing COVID-19 pandemic, that might likely amplify this pattern, as argued by Okyere *et al.* (2020) for the cases of epidemic interactions, communications and meal delivery in China. Relatedly, Prettner and Bloom (2020) point out that the "hollowing out" effect of robots and automation is expected to be reinforced by the COVID-19 pandemic, while Leduc and Liu (2020) discusses how the pandemic-induced uncertainty about workers productivity may further trigger automation adoption. Muro *et al.* (2020) stress how "*Robots' infiltration of the workforce doesn't occur at a steady, gradual pace*" but is "*concentrated especially in bad times such as in the wake of economic shocks, when humans become relatively expensive as firms' revenues rapidly decline*". Ultimately, the rising concerns about the replacement of workers by this new wave of labour-saving technological change is even leading scholars to support robot taxation (e.g., Costinot and Werning, 2018; Thuemmel, 2018; Guerreiro *et al.*, 2020).[1]

A growing literature is currently dealing with the effects of robotisation (and even more generally of automation) on various labour market outcomes: unemployment, participation, along with wage and inequality effects. At the same time, there has been a rising use of skills within the production process. For instance, the raw percentages of hours worked by skilled labour has increased by 6% on average across both sectors and countries, while the ones worked by unskilled

[1] On the other hand, it should be acknowledged the positive role potentially and effectively played by robots during the COVID-19 outbreak, especially in terms of public health and services, addressing risks of infectious diseases, disinfection, surgical procedures, delivering foods and medication, as argued, among others, by Yang *et al.* (2020), Khan *et al.* (2020) and Tavakoli *et al.* (2020).

labour dropped by 7% in the 1995-2005 period (see Battisti *et al.*, 2020). These two phenomena are jointly assessed in the race between technology and education, pioneered by Tinbergen (1974) and further explored by Goldin and Katz (2009), Autor *et al.* (2020) and many others. As we show later, the share of robotic capital has dramatically increased from the '90s till to the end of the following decade of about 40%, reaching percentages of more than 2.5% in some industrial sectors in countries such as Japan, Germany, Italy and Spain, where a lot of job routines are robotised or automated.

We focus on these issues by investigating whether robotic capital is complementary to some kinds of skills. In so doing, we take into account other forms of capital and a wide array of skill types. Particularly, we build a specific stock of robotic capital and include it into different types of production functions at the country-sector level, distinguishing between robotic, ICT capital and the remainder. The robustness of our results are assessed using two different datasets and analysis frameworks. Our primarily dataset includes 7,099 observations, matched over 35 countries and 17 sectors (based on WIOD, 2015), while a secondary, and smaller dataset, includes 2,169 observations, matched over 15 countries and 17 sectors (based on EU KLEMS, 2009).

To the best of our knowledge, the present study represents the first attempt for investigating complementarity/substitutability between different kinds of automatised capital and skill types, from a country-industry perspective. In this respect, the main contributions of the study can be summarised as follows:

1. The robotic capital-skill complementarity hypothesis is examined using different samples, frameworks of analysis and parametric regression methods. Our main findings point to lower elasticities of substitution between robotic capital and skilled labour, i.e. more complementarity;

2. We find some hints of independent, polarising effects produced by robotic capital;

3. Such findings are extended and generalised by employing robotic, ICT and other capital, and three skill types to looking for heterogeneous roles of elasticity in wage polarisation, following Acemoglu and Autor (2011).

The rest of the paper is organised as follows. Section 3.2 presents a survey about the recent theoretical and empirical works dealing with automation and robotisation issues; Section 3.3 briefly illustrates the datasets construction, providing information on the main variables used throughout the analysis, as well as several insights with respect to the trends of robotisation within the labour market; Section 3.4 sets up the basic analysis framework; Section 3.5 presents and discusses the benchmark empirical results obtained relying upon recent parametric approaches in the literature; Section 3.6 deals with the sensitivity analysis, carried out by differently computing some of the main variables; Section 3.7 investigates whether robotic capital equipment produces independent, polarising effects, while Section 3.8 contains concluding remarks.

## 3.2 Robotisation and labour market related literature

This paper speaks to different strands of literature. First, it is inspired by works on automation and labour market outcomes, such as productivity, wages and unemployment, whereby efforts by researchers have been devoted in both the modelling and testing the impact of automation technologies, of which robotisation represents a subset.

From a theoretical standpoint, starting from the seminal work of Zeira (1998), the concerns recently posed by analysts and scholars on the consequences of the rapid outbreak of artificial intelligence, digital technologies and robots on labour market have prompted many studies on this field.[2] For instance, by developing a dynamic general equilibrium model incorporating investments in both robots and traditional capital, Berg *et al.* (2018) state that automation produce two contrasting effects: positive for growth and negative for equality. Analogously, the growth model of directed technical change[3] proposed by Hemous and Olsen (2014),

[2] Such concerns have been summarised in the expression "*Is this time different?*" by several contributions, such as Mokyr *et al.* (2015), Furman (2016) and Balsmeier and Woerter (2019), amongst others.

[3] On this point see, for instance, Acemoglu (1998, 2002).

with machines complementing (replacing) high-skilled (low-skilled) labour and horizontal innovations (namely, the introduction of new products, which raises the demand for both skill types), leads to stagnating wages for low-skilled workers and intensification of wage disparities. Moll *et al.* (2019) argue that automation may exacerbate inequality via increasing returns to wealth, in a theoretical model linking technology to personal income and wealth distributions. A more optimistic view is instead presented by Nakamura and Zeira (2018), who develop a task-based model where all labour tasks are automatised if wages are adequately high: nonetheless, if the number of new jobs created grow sufficiently fast, the share of jobs mechanised each period shrinks and unemployment stemming from automation declines and converges to zero in the long-run.

Meanwhile, although the growing empirical literature is attempting to address the many concerns regarding the impact of robotisation on labour market outcomes, the evidence is far from clear-cut. For instance, pioneering works by Acemoglu and Restrepo (2020) and Graetz and Michaels (2018), employing new data from the International Federation of Robotics (IFR) on operation industrial robots, point to, respectively, a harmful effect of robotics on wages and employment in the US labour market from 1990 to 2007 and a favourable influence on productivity growth in 17 economies spanning the period 1993-2007. Contrary to the non-significant association between robotisation and total employment in Graetz and Michaels (2018), de Vries *et al.* (2020) provide evidence of a strong decline in the employment share of routine manual task-intensive jobs in a panel of 37 countries and 19 sectors over the years 2005-2015. On the same line, Chiacchio *et al.* (2018) report that the adverse impact of robot adoption comes at the expense of middle-educated workers. Similarly, by introducing an indicator for the ability of robots to execute different tasks, Carbonero *et al.* (2020) observe a strong, negative effect on worldwide employment, especially in emerging economies.[4] Positive impacts of robotisation on

[4] As further evidence from a single country perspective, Faber (2020) observes a robust negative influence of robotisation on employment within the Mexican labour market, in particular for men and low-skilled workers. Relatedly, Lankisch *et al.* (2019) and Dixon and Lim (2020) argue that automation can be considered as a crucial factor in explaining, respectively, the rising inequality and the decline of the US labour share. With specific reference to Portugal, Fonseca *et al.* (2018) point out job polarisation as a result of rising automation and computerisation. Conversely, Dauth *et al.* (2018) show sectoral adjustments in the composition of total employment in German labour

employment are instead found by Klenert *et al.* (2020) and De Backer *et al.* (2018) in Europe and within MNEs, respectively. Opposite findings are highlighted by Compagnucci *et al.* (2019) in a panel of manufacturing industries of 16 OECD countries, with robots positively (negatively) correlated with the growth of hourly wages (hours worked). Likewise, Blanas *et al.* (2020) show that robots are associated with a decreasing (increasing) demand for the young, women, low- and medium-skilled workers (men, older and high-skilled workers).

Overall, it can be noticed that the empirical literature on this field usually produces mixed results, with evidences of drops in employment and participation, that may be temporary or focused in some sectors or for specific skills.

The second line of research examines the issues of inequality, whose contributions starting from Katz and Murphy (1992) and the literature on skill-biased technical change point to different substitutability degrees for skilled and unskilled workers, as in the recent work of Caselli (2016). Alongside these themes, this paper is related (to a limited extent) to the polarisation of the labour force framework, namely the documented process, starting from the 1980s, for which employment has gradually becoming clustered at the tails of the occupational skill distribution (see, for instance, Acemoglu, 1999; Autor *et al.*, 2006; Goos *et al.*, 2009; Acemoglu and Autor, 2011). Such a framework is based upon the so-called routine-biased technical change hypothesis (Autor *et al.*, 2003), whereby the "hollowing out" effect of automation leads to the disappearance of jobs requiring a well-defined set of repetitive tasks, typically assigned to middle-skilled workers.[5]

Furthermore, a relevant number of studies deals with problems of capital-skill complementarity at a general level of capital, such as Griliches (1969), Fallon and Layard (1975), Duffy *et al.* (2004) and Henderson (2009), whereas Krusell *et al.* (2000), Raveh and Reshef (2016), Eden and Gaggl (2018) and Taniguchi and Yamada (2019) investigate the effects of specific, non-neutral kinds of capital equipment. The evidence from this literature typically validates the hypothesis of more complementarity between capital and skilled workers. In particular, Krusell

markets over the years 2004-2014, with the creation of additional service sector jobs offsetting the losses in manufacturing industry.

[5] Additional empirical evidence in this direction is provided, among others, by David and Dorn (2013), Michaels *et al.* (2014), Jaimovich and Siu (2020) and vom Lehn (2020).

*et al.* (2000) analyse the phenomenon under investigation in the direction of this paper, by disaggregating capital in structures and equipment, finding the latter as less substitutable with skilled workers. On the same line, by paying attention to developing economies, Raveh and Reshef (2016) find that only R&D capital is complementary to skilled labour, while less innovative capital is complementary to unskilled. Analogously, Taniguchi and Yamada (2019) and Eden and Gaggl (2018) observe similar results for ICT capital in a panel of OECD countries and US, respectively. Lastly, Dao *et al.* (2020) argue that the downward trend of the labour share of income can substantially be explained by the high substitutability between routinised jobs and computer capital.

An additional stream of research stresses how much of technical progress is incorporated or neutral with respect to the capital, stemming from the argument on embodied and disembodied technical progress, revamped by Greenwood *et al.* (1997) and Hercowitz (1998). Recently, Battisti *et al.* (2018) observe that technical progress measured by capital returns is bigger than the Hicks-neutral technology improvements, differently from previous findings by Sakellaris and Wilson (2004). This could be even more severe with robotic capital, insofar as the embodied content of technical progress may be higher, for instance, than ICT or other capital equipment. Moreover, Caselli and Manning (2019) show how under the assumption of a reduction of the relative price of investment goods driven by the new technology, the existing capital return will drop, implying a higher return for labour. The crucial empirical question, in such context, is whether and what workers benefit from this new wave of technological advances.

Finally, the complementarity/substitutability argument is important in the reversal discussion of technology adoption pioneered by Krugman (1979), because if a productive factor, such as unskilled labour, becomes less complementary to capital and the latter is increasingly more relevant in the production process, then this is equivalent to a higher opportunity cost for such factor, implying greater demand for unskilled labour saving technology, as in Koeniger and Leonardi (2007) or Alesina *et al.* (2018).

## 3.3 Data

In this section, we provide a brief overview of the relevant data used to carry out the present study (3.3.1), as well as a set of descriptive findings surrounding the relationship between the rise of automated capital and workers' replaceability (3.3.2).

### 3.3.1 The datasets

The empirical analysis builds upon the integration of data from different sources. In particular, we exploit information on robots from the Industrial Federation of Robotics (IFR, 2019), and merge these data with both WIOD (2015) and EU KLEMS (2009), encompassing information on worker types, capital assets and value added, among others.[6] In so doing, we derive two distinct datasets on which the robotic capital-skill complementarity hypothesis can be tested. The WIOD dataset contains 7,099 observations, matched over 35 countries and 17 industries spanning the period 1997-2009, whereas the EU KLEMS dataset includes 2,169 observations, matched over 15 countries and 17 industries for the years 1997-2005.[7]

The main variables employed throughout the empirical analysis are:

- Robotic capital stock, $K_r$. Data on stock, deliveries and average unit price of operational industrial robots are retrieved from the World Robotics: Industrial Robots and Service Robots (IFR, 2019). Following Graetz and Michaels (2018), we compute the robot stock (i.e., quantities) for each country-sector pairs using the perpetual inventory method based on robot deliveries (i.e., investments) and assuming a depreciation rate of 10 per-

[6] Data on operational stock and deliveries of robots are provided by IFR (2019) according to ISIC Rev. 4 industry classification, contrary to ISIC Rev. 3.1 characterising both the WIOD (2015) and EU KLEMS (2009) datasets. In order to merge the different coded sources, we make use of a correspondence table to convert IFR data from ISIC Rev. 4 to ISIC Rev. 3.1 industry classification.

[7] The set of countries, industries and time periods, driving the construction of the two datasets, are dictated by data availability. The list of countries and industries, as a result of the matching process, is reported in Section C2 of the Appendix.

cent.[8] Specifically, we calculate $R^S_{cit} = R^D_{cit} + (1-\delta)R^S_{cit-1}$, where $c$, $i$ and $t$ represent country, industry and time, respectively; $R^S$ and $R^D$ denote, respectively, the stock and deliveries of robots, whereas $\delta$ is the depreciation rate. Consequently, $K_r$, is obtained by

$$K_{r,cit} = \frac{R^S_{cit} * R^P_{ct}}{D_{cit}}$$

where $R^P$ represents the average unit price of industrial robots and $D$ is the capital deflator;[9]

- Total capital stock, $K$, and value added, $Y$, from WIOD (2015) or EU KLEMS (2009);
- Non-robotic capital, $K_{nr}$, from WIOD (2015) or EU KLEMS (2009), computed as the difference between total ($K$) and robotic capital stock ($K_r$);
- ICT and other capital stock, $K_i$ and $K_o$, respectively, from EU KLEMS (2009), as additional, disaggregated measures of capital;
- High-, medium- and low-skilled workers, WIOD (2015) or EU KLEMS (2009), expressed in terms of hours worked ($L$), hourly wages ($w$), income and hours shares ($sL$ and $L^s$), depending on the specific estimated models.

All variables are expressed in real prices and PPP adjusted 2005 international dollars, using the PPP conversion factor from Inklaar and Timmer (2014). Descriptive statistics, based on both the WIOD (2015) and EU KLEMS (2009) datasets, are reported in section C3 of the Appendix.

### 3.3.2 Robotic capital penetration in advanced economies

The stock of robotic capital has risen substantially in advanced economies over the past decades. To have an apples-to-apples comparison, the total real capital

[8] As in Graetz and Michaels (2018), to check the robustness of our findings, the robotic capital variable is also constructed using depreciation rates of 5 and 15 percent.

[9] The complete strategy used to measure robotic capital stock is detailed in section C1 of the Appendix.

evolution in the period 1997-2009 from Penn World Table 9.1 (Feenstra *et al.*, 2015) shows an increase on the order of 65% in Spain, 30% for countries as Italy, Japan and Germany. The same countries on average doubled the robotic capital (in the case of Spain, it increased almost three times). Additionally, United States witnessed a more substantial growth around 150%. Such an expansion was driven, in particular, by strong robotic investments in the rubber and plastic, wood products, electronics and transport equipment industrial sectors.[10]

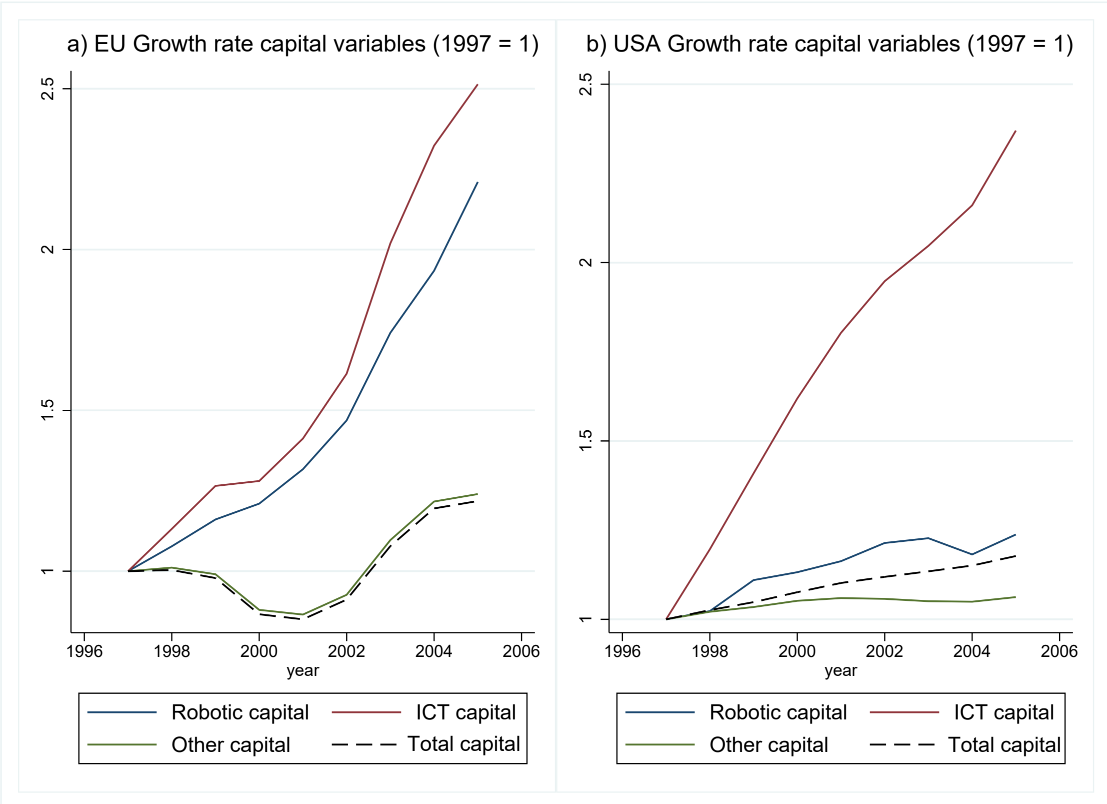



Figure 3.1: Capital stock evolution, 1997-2005

Figure 3.1 indicates that the evolution of automatised capital (ICT and robotic) has been much bigger than the rest either in USA or EU. In the latter, the robotic

[10]The robotic capital evolution for a subset of countries and industries is provided in section C3 of the Appendix.

capital dynamics have been almost the same as that of ICT.[11]

On this point, as shown in panel a) of Figure 3.2 below, in the period under investigation the share of robotic capital has touched peaks of about 2.5%-3% in Japan, Spain, Italy and Germany, as well as in wood products, electronics and transport equipment industries (ISIC Rev. 3.1 codes 20, 30t33 and 34t35, respectively), in panel b) of Figure 3.2.[12]

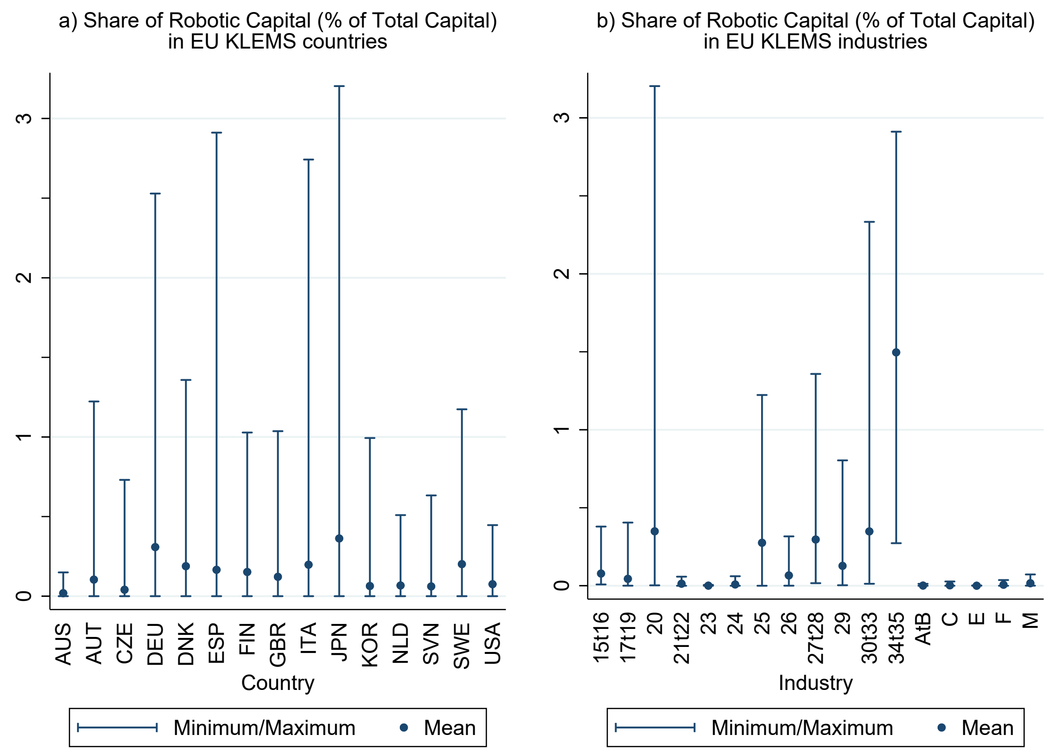



Figure 3.2: Share of robotic capital
in EU KLEMS countries and industries, 1997-2005

What this tells us is that the capital composition of production factors shifted toward a more intensive use of robots, as further highlighted in Figure 3.3 below. Looking to the stock of robots over workers deepening - the so-called *robot density*,

[11]A similar trend is highlighted by Schivardi and Schmitz (2018) for ICT capital in a sample of OECD economies.

[12]Code descriptions of the ISIC Rev. 3.1 industries are reported in Table C2.2 of the Appendix.

as in Graetz and Michaels (2018) - in the period 1995-2017 the growth continues steadily the tendency, either looking to hours worked, or to number of employees.[13] Such descriptive evidence suggests that the share of robotic capital, as pointed out in Figure 3.1, may have grown up following a similar trend.

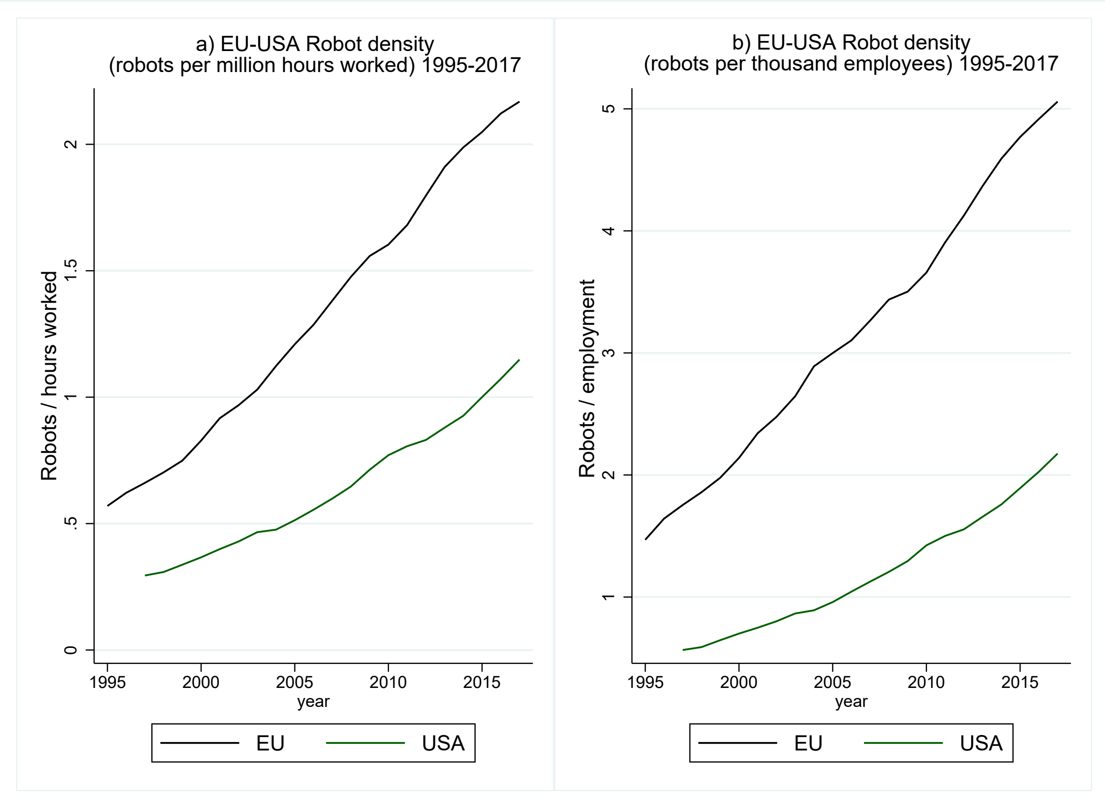



Figure 3.3: Robot density, 1995-2017

The increased robotisation of the production process raises the question about relative prices and directed technical change. Figure 3.4 shows that the relative current price ratio of robots versus workers strongly and steadily decreased in two countries for which we have original price data. The difference is interesting because while in Germany the decrease continued after 2005, in the USA the series

[13]Being not constrained by robot prices data, the robot density variables are computed using the EU KLEMS (2019) release (Adarov and Stehrer, 2019; Stehrer *et al.*, 2019) to exploit the full length of the IFR series on stock of industrial robots.

became flat. One possible interpretation is that in a country with more flexible wages, the usually rigid nominal floor is less binding than in another with more stringent labour market institutions.

To sum up, we see how: i) robotic capital grew more than the rest of capital (almost in line with ICT), ii) the robotic capital deepening was strong, iii) the relative prices of robots went down. These descriptive findings suggest a strong pressure on workers that in some countries may be satisfied through price reduction (typically in real terms) and in other through quantity reduction, which happens to be the usual outcome analysed in the extant literature.

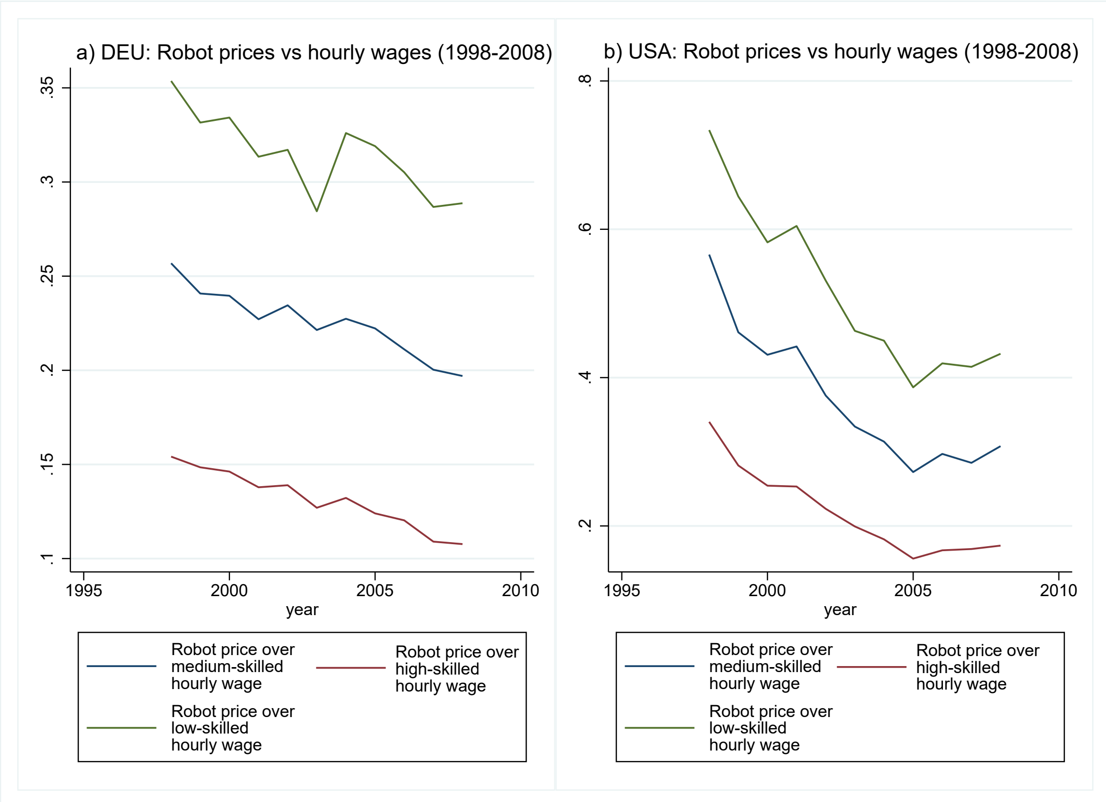



Figure 3.4: Relative cost of robots, 1998-2008

This way we wonder which kind of workers may be more substitutable by robots, with respect their marginal products (proxied by wages) and their complementarity with respect to robots. The latter issue follows, for example, the intuition of Acemoglu and Autor (2011) about the mechanised and/or routinised tasks that may be replaceable by machines. If medium-skilled workers were, for instance, more replaceable by robotic capital, this process should drive towards wage polarisation and increasing inequality, as pointed out in France by Davis *et al.* (2020).

## 3.4 Robotisation and skill composition change

In the light of what has emerged in the descriptive evidence presented previously, the content of following sections provides an overview of the frameworks aimed at measuring the elasticities of substitution between different types of capital and skills.

### 3.4.1 Production function with different types of capital

A standard framework to investigate the elasticity of substitution between labour types is the nested constant elasticity of substitution (CES) production function (removing subscripts for countries, industry and time to ease notation), as in Violante (2016):

$$Y = AK^{\alpha}\left[(A_s L_s)^{\sigma} + (A_u L_u)^{\sigma}\right]^{\frac{1-\alpha}{\sigma}} \tag{3.1}$$

where $Y$ represents aggregate output; $A$ is a Hicks-neutral efficiency parameter; $A_s$ and $A_u$ denote factor specific productivities; $K$, $L_s$ and $L_u$ indicate the capital stock, skilled and unskilled labour, respectively; parameters $\alpha$ and $\sigma$ govern the elasticities of output to capital and between labour types, respectively. By assuming competitive capital and labour markets, the log-transformation of marginal rate of technical substitution (MRTS) between the two labour inputs yields:

$$\ln\left(\frac{\partial Y/\partial L_s}{\partial Y/\partial L_u}\right) = \sigma \ln\left(\frac{A_s}{A_u}\right) + (\sigma - 1)\ln\left(\frac{L_s}{L_u}\right) + \epsilon \tag{3.2}$$

In this formulation, by reasonably assuming $\sigma > 0$, an increase in the (unobserved) ratio $A_s/A_u$ is associated with the skill-biased technical change (SBTC). Therefore, a regression estimation of a general form as in (3.2), with the left-hand side replaced by the skill-premium, entails an identification issue of the constant term, $\sigma$, due to the unknown right-hand side first term, $A_s/A_u$. Consequently, one has to *a priori* fix either the SBTC term or the elasticity of substitution to obtain the other parameter residually (Diamond *et al.*, 1978). Additionally, the capital stock is assumed as neutral by the model with respect to the skill types, not allowing the evaluation of the capital-skill complementarity hypothesis - in other terms, whether and how capital is more or less complementary to different labour inputs.

To overcome these issues, we need a more general framework which enables incorporating distinct kinds of capital and derive different substitutability degrees among factor inputs. An example is offered by the Krusell *et al.* (2000) aggregate production function, encompassing two types of capital: structures, $K_s$, which is neutral with respect to the skill types, and equipment, $K_e$, considered as non-neutral:

$$Y = K_s^{\alpha}\left[\lambda[\mu(K_e)^{\rho} + (1-\mu)(L_s)^{\rho}]^{\frac{\sigma}{\rho}} + (1-\lambda)(L_u)^{\sigma}\right]^{\frac{1-\alpha}{\sigma}} \tag{3.3}$$

where $\lambda$ and $\mu$ are distribution parameters, and $\rho$ and $\sigma$ govern the elasticity of substitution between $K_e$ and $L_s$, and between the $K_e$-$L_s$ composite and $L_u$.

By once again assuming that the markets for inputs are competitive, the first-order conditions of profit-maximising behaviour and price-taking firms imply the following (approximate) skill-premium relationship:

$$\ln\left(\frac{w_s}{w_u}\right) \simeq \lambda\frac{\sigma-\rho}{\rho}\ln\left(\frac{K_e}{L_s}\right)^{\rho} + (\sigma-1)\ln\left(\frac{L_s}{L_u}\right) \tag{3.4}$$

Krusell *et al.* (2000) replicate the model in (3.4) on US series of capital and labour over the years 1963-1992 and consistently find $\sigma > \rho$, suggesting that the relative demand for skilled workers increased with the stock of capital equipment. Insofar as the SBTC is reflected into the rapid growth of capital equipment, the capital-skill complementarity implies an increase (decrease) of the marginal product of skilled (unskilled) labour, which in turn exacerbates wage inequality. According to the functional form reported in (3.3), it is possible to get an answer to the question about more or less complementarity between different types of capital and labour. In the light of this, our framework might consider two scenarios:

1. The simplest one deals with two types of capital, as in Krusell *et al.* (2000), namely robotic capital equipment, $K_r$ and the remainder, non-robotic capital, $K_{nr}$. The framework would be similar to (3.3), but this would imply the crucial assumption of treating $K_{nr}$ as completely neutral with respect

to different skills. Nonetheless, due to data availability - especially from a macro perspective - and constraints imposed by the functional forms, there are not many ways to overcome this issue. An alternative is provided by Raveh and Reshef (2016), who propose a model in which composed goods are obtained, respectively, by two types of workers, skilled and unskilled, and two types of capital, such as computers and tractors. However, the critical assumption underlying this procedure is that each kind of capital is more complementarity to one skill type than with the other - i.e., computers (tractors) are complementary only to skilled (unskilled) labour. Such an assumption represents the main shortcoming of this framework, as we cannot *a priori* postulate, for instance, that the elasticity of robotic capital equipment and skilled labour is the same than ICT capital and unskilled labour. In this respect, Eden and Gaggl (2018), building upon the contribution of Krusell *et al.* (2000), relax the strong assumption contained in Raveh and Reshef (2016), by implementing a Cobb-Douglas aggregate of non-ICT capital and a composite input produced by a nested CES combination of ICT capital (assumed as a subset of the general category of capital equipment) and two types of labour. Such a formulation turns out to be suitable in our case, as we can replace ICT with robotic capital and test our capital-skill complementarity hypothesis. The same applies for the four-factors production function proposed by Taniguchi and Yamada (2019), where the complementarity hypothesis is tested by pairing ICT capital equipment with skilled labour, *à la* Krusell *et al.* (2000). Once again, by properly replacing and pairing robotic capital in such a model specification, this framework makes it possible to test whether robotic capital is less substitutable with skilled than unskilled workers;[14]

2. In the most complete setting, we might be able to explore the capital-skill complementarity hypothesis along multiple dimensions, by disentangling the contributions of three types of capital - i.e., robotic, ICT and other capital stock - as well as three labour types. In so doing, the six-factors production function developed by Taniguchi and Yamada (2019) allows to achieve this

[14]Detailed derivations of both the Eden and Gaggl (2018) and Taniguchi and Yamada (2019) models, adjusted to our analysis, are provided, respectively, in sections C4 and C5 of the Appendix.

goal. Specifically, in their model output is produced by a technology using two different forms of non-neutral capital equipment, ICT and non-ICT, a third, neutral kind of structures capital, and three workers types (i.e, high-, medium- and low-skilled labour). By pairing ICT with high-skilled and non-ICT capital with low-skilled labour, Taniguchi and Yamada (2019) find broad confirmation of the ICT (plus non-ICT) capital-skill complementarity hypothesis in a panel of 14 OECD countries over the years 1970-2015. By suitably replacing the two capital equipment types, we can adapt this framework and apply it to our case study, looking for different elasticities of substitution stemming from pairing robotic capital equipment with high-skilled and ICT capital equipment with low-skilled workers - i.e., the robotic plus ICT capital-skill complementarity hypothesis. According to the International Standard Industrial Classification of all Economic Activities (ISIC Rev. 4, 2008), robots are group under 'general-purpose machinery', specifically under 'lifting and handling equipment' and 'other special-purpose machinery'. As these are reported within the broader heading of machinery (i.e., non-ICT capital), robots are not part of ICT capital, which covers computers and telecommunication equipment.[15] Consequently, we avoid overlapping the two types of capital and independently analyse their complementarity/substitutability effects, as it will be shown in the following section. In addition, within the six-factors production function framework, we can relax (at least to some extent) the strong assumption underlying the four-factors specification built upon the Krusell *et al.* (2000) framework.

In order to produce a more in-depth investigation of the broader capital-skill complementarity hypothesis, in the next section we also consider its empirical evaluation in the spirit of Duffy *et al.* (2004), by pairing the total capital stock with skilled labour and testing the complementarity hypothesis from a country-sector perspective. Subsequently, we present and briefly discuss the robotic capital-skill complementarity hypothesis relying upon the Eden and Gaggl (2018) and Taniguchi and Yamada (2019) procedures.

[15] We are grateful to Robert Inklaar for his comment on this point.

## 3.5 Econometric Analysis

In this section, we empirically assess the total and robotic capital-skill complementarity hypotheses. Specifically, by employing parametric nonlinear estimations, we first test the total capital-skill complementarity hypothesis, building on the procedure designed by Duffy *et al.* (2004) and, subsequently, investigate the robotic capital-skill complementarity hypothesis according to the Eden and Gaggl (2018) and Taniguchi and Yamada (2019) frameworks.[16] Throughout the benchmark econometric analysis, the unskilled labour category is obtained by aggregating medium- and low-skilled workers. In the robustness section, we check whether the results turn out to be sensitive either when medium-skilled are group together with high-skilled workers.

### 3.5.1 Parametric nonlinear models and estimation strategy

In the first step of our empirical analysis, we follow Duffy *et al.* (2004) and assess the total capital-skill complementarity hypothesis relying upon a two-level CES production function of the form:

$$Y_{cit} = A_{c0}\left\{a[bK^{\rho}_{cit} + (1-b)L^{\rho}_{s,cit}]^{\frac{\sigma}{\rho}} + (1-a)L^{\sigma}_{u,cit}\right\}^{\frac{1}{\sigma}} e^{\lambda t+\varepsilon_{cit}} \tag{3.5}$$

where $c$, $i$ and $t$ represent country, industry and time, respectively; $Y$ is the aggregate output; $A_{ci0}$ denotes the exogenous, Hicks-neutral technology, growing at rate $\lambda$ for country $c$ at time $t = 0$; $a$ and $b$ indicate distribution parameters; $K$ is the total capital stock; $L_s$ and $L_u$ denote hours worked by skilled and unskilled labour, respectively, and $\varepsilon$ is the error term. The elasticity of substitution between capital stock and skilled labour is given by $1/(1-\rho)$, while $1/(1-\sigma)$ represents the elasticity of substitution between the $K$-$L_s$ composite and unskilled labour. As in the benchmark version of Duffy *et al.* (2004), the model in (3.5) is estimated using nonlinear least squares (NLLS) on both the WIOD and EU KLEMS samples.

The second step involves the Eden and Gaggl (2018) specification, where we test

[16] To save space, in the test we present only the estimated models, providing their detailed derivation in the Appendix.

the robotic capital-skill complementarity hypothesis by simultaneously estimating the following system of two equations:

$$\ln\left(\frac{sK_{r,cit}}{sL_{s,cit}}\right) = \ln\left(\frac{\gamma}{1-\gamma}\right) + \rho \ln\left(\frac{K_{r,cit}}{L^{s}_{s,cit}}\right) + \epsilon_{1,cit} \tag{3.6}$$

$$\ln\left(\frac{sL_{u,cit}}{sZ}\right) = \ln\left(\frac{\beta}{1-\beta}\right) + \sigma \ln\left(\frac{L^{s}_{u,cit}}{Z}\right) + \epsilon_{2,cit} \tag{3.7}$$

where $K_r$ is robotic capital; $L^s_s$ and $L^s_u$ represent the shares of hours worked by skilled and unskilled labour, respectively; $Z = \left\{\gamma K^{\rho}_{r,cit} + \left[1-\gamma\right](L^{s}_{s,cit})^{\rho})\right\}^{\frac{1}{\rho}}$ is the composite term comprising robotic capital and skilled labour; $sK_r$, $sL_s$, $sL_u$, $sZ$ denote the income shares of $K_r$, $L^s_s$, $L^s_u$ and $Z$, respectively; $\beta$ and $\gamma$ indicate distribution parameters, while $\epsilon_1$ and $\epsilon_2$ are the error terms, allowed to be correlated across equations. The elasticity of substitution between robotic capital and skilled labour, $1/\left(1-\rho\right)$, is derived by equation (3.6), while the elasticity of substitution between the $K_r$-$L^s_s$ composite (i.e., $Z$) and unskilled labour, $1/(1-\sigma)$, is identified from equation (3.7).

In the third step, following Taniguchi and Yamada (2019), we further explore the robotic capital-skill complementarity hypothesis by employing the four- and six-factors production functions. The four-factors specification is jointly estimated according to the following system of two equations:

$$\Delta \ln\left(\frac{w_{s,cit}}{w_{u,cit}}\right) = \underbrace{-(1-\sigma)\Delta \ln\left(\frac{L_{s,cit}}{L_{u,cit}}\right)}_{\text{quantity effect}} + \underbrace{\frac{\sigma-\rho}{\rho}\Delta \ln\left[\left(\frac{K_{r,cit}}{L_{s,cit}}\right)^{\rho} + 1\right]}_{\text{complementarity effect}} + u_{1,cit} \tag{3.8}$$

$$\Delta \ln\left(\frac{w_{s,cit}}{r_{r,cit}}\right) = -\left(1-\rho\right)\Delta \ln\left(\frac{L_{s,cit}}{K_{r,cit}}\right) + u_{2,cit} \tag{3.9}$$

where $w_s/w_u$ is the skilled-to-unskilled relative wage; $L_s$ and $L_u$ indicate, respectively, hours worked by skilled and unskilled labour; $K_r$ is the robotic capital; $r_r$ represents the rental price of robotic capital,[17] while $u_1$ and $u_2$ are idiosyncratic

[17]Further information on the computation of rental price of capital are reported in subsection C5.3 of the Appendix.

errors, allowed to be correlated across equations. The elasticity of substitution between skilled and unskilled workers, $1/(1-\sigma)$, is identified from equation (3.8), while the elasticity of substitution between robotic capital and skilled workers, $1/\left(1-\rho\right)$, is derived by equation (3.9).

Finally, the six-factors production function, proposed by Taniguchi and Yamada (2019), is simultaneously estimated according to the following system of four equations:

$$\Delta\ln\left(\frac{w_{h,cit}}{w_{m,cit}}\right) = \underbrace{-(1-\sigma)\Delta\ln\left(\frac{L_{h,cit}}{L_{m,cit}}\right)}_{\text{quantity effect}} +$$

$$\underbrace{\frac{\sigma-\rho}{\rho}\Delta\ln\left[\left(\frac{K_{r,cit}}{L_{h,cit}}\right)^{\rho}+1\right]-\frac{\sigma-\xi}{\xi}\Delta\ln\left[\left(\left(\frac{K_{i,cit}}{L_{m,cit}}\right)^{\eta}+\left(\frac{L_{\ell,cit}}{L_{m,cit}}\right)^{\eta}\right)^{\frac{\xi}{\eta}}+1\right]}_{\text{complementarity effect}} + v_{1,cit} \tag{3.10}$$

$$\Delta\ln\left(\frac{w_{m,cit}}{w_{\ell,cit}}\right) = \underbrace{-(1-\xi)\Delta\ln\left(\frac{L_{m,cit}}{L_{\ell,cit}}\right)}_{\text{quantity effect}} + \underbrace{\frac{\eta-\xi}{\eta}\Delta\ln\left[\left(\frac{K_{i,cit}}{L_{\ell,cit}}\right)^{\eta}+1\right]}_{\text{complementarity effect}} + v_{2,cit} \tag{3.11}$$

$$\Delta\ln\left(\frac{w_{h,cit}}{r_{r,cit}}\right) = -\left(1-\rho\right)\Delta\ln\left(\frac{L_{h,cit}}{K_{r,cit}}\right) + v_{3,cit} \tag{3.12}$$

$$\Delta\ln\left(\frac{w_{\ell,cit}}{r_{i,cit}}\right) = -\left(1-\eta\right)\Delta\ln\left(\frac{L_{\ell,cit}}{K_{i,cit}}\right) + v_{4,cit} \tag{3.13}$$

where $w_h/w_m$ and $w_m/w_\ell$ represent the relative wages of high- to medium- and medium- to low-skilled labour, respectively; $L_h$, $L_m$ and $L_\ell$ indicate, respectively, hours worked by high-, medium- and low-skilled labour; $K_r$ and $K_i$ represent robotic and ICT capital equipment, respectively; $r_r$ and $r_i$ are the rental prices of robotic and ICT capital equipment, respectively, while $v_1$, $v_2$, $v_3$, and $v_4$ are idiosyncratic errors, allowed to be correlated across equations. The elasticity of substitution between high- and medium-skilled labour, $1/(1-\sigma)$, is derived from equation (3.10), while the elasticity of substitution between robotic capital and high-skilled labour, $1/\left(1-\rho\right)$, is identified from equation (3.12). The elasticity of substitution between medium- and low-skilled labour, $1/(1-\xi)$, is derived from equation (3.11), while the elasticity of substitution between ICT capital equipment and low-skilled labour, $1/(1-\eta)$, is identified from equation (3.13).

The total capital-skill complementarity hypothesis for Duffy *et al.* (2004), in (3.5), as well as the robotic capital-skill complementarity hypothesis for Eden and Gaggl (2018), in (3.6)-(3.7), and Taniguchi and Yamada (2019), in (3.8)-(3.9), (3.10) and (3.12), are verified if

$$1/(1-\rho) < 1/(1-\sigma) \implies \sigma > \rho.$$

Ultimately, for the six-factors model by Taniguchi and Yamada (2019), the ICT capital-skill complementarity hypothesis, in (3.11) and (3.13), is verified if

$$1/(1-\xi) < 1/(1-\eta) \implies \eta > \xi.$$

Both the Eden and Gaggl (2018) and Taniguchi and Yamada (2019) approaches, in equations (3.6)-(3.7), (3.8)-(3.9) and (3.10)-(3.13), respectively, are tested employing the generalised method of moments (GMM) estimation technique, treating all the input factors as endogenous and using their lagged values as instruments.[18]

### 3.5.2 Benchmark estimation results

Table 3.1 reports the results of our benchmark estimates. The total capital-skill complementarity hypothesis, analysed according to equation (3.5), is only confirmed when tested on the EU KLEMS sample. Such a partial evidence is in line with the existing empirical literature (e.g., Fallon and Layard, 1975; Duffy *et al.*, 2004; Papageorgiou and Chmelarova, 2005; Henderson, 2009), being dependent, for instance, on data availability and/or measurement, country-time coverage and estimation techniques. Additionally, the non-distinction between capital structures, assumed as neutral, and capital equipment, which increases (decreases) the

[18] The Eden and Gaggl (2018) procedure can be applied on both the WIOD and EU KLEMS samples, as we can rely upon the constructed measures of non-robotic capital. By contrast, the Taniguchi and Yamada (2019) models can only be estimated by employing the EU KLEMS sample, due to the availability of data on the industry rate of return on capital (IRR) which is necessary for computing the rental prices of capital in equations (3.9), (3.12) and (3.13), as well as the disaggregation of capital stocks between ICT and other assets for the six-factors model specification.

marginal product of skilled (unskilled) labour, may dramatically impact the results.

**Table 3.1:** Estimated elasticities of substitution

| Production functions | $1/(1-\rho)$ | $1/(1-\sigma)$ | $1/(1-\xi)$ | $1/(1-\eta)$ | Obs. |
|---|---|---|---|---|---|
| Duffy et al. (2004) WIOD sample (1997-2009) | 0.599 | 0.557 | | | 6426 |
| Duffy et al. (2004) EU KLEMS sample (1997-2005) | 0.678 | 0.863 | | | 1872 |
| Eden and Gaggl (2018) WIOD sample (1997-2009) | 2.649 | 4.143 | | | 3468 |
| Eden and Gaggl (2018) EU KLEMS sample (1997-2005) | 9.236 | 28.313 | | | 1344 |
| Taniguchi and Yamada (2019) four factors | 6.254 | 7.652 | | | 431 |
| Taniguchi and Yamada (2019) six factors | 1.141 | 2.284 | 1.333 | 1.192 | 147 |

*Notes*: The estimated coefficients and standard errors are reported in Table C6.1 of the Appendix.

In this respect, once we differentiate between robotic and other capital assets, we find broad confirmation of the robotic capital-skill complementarity assumption. Specifically, the Eden and Gaggl (2018) procedure points to this direction when applied to both the WIOD and EU KLEMS samples, where the elasticity of substitution between the robotic-capital and skilled labour, $1/(1-\rho)$, is lower than between the $K_r$-$L_s$ composite and unskilled labour, $1/(1-\sigma)$, which implies $\sigma > \rho$. Likewise, our findings corroborate the robotic capital-skill complementarity hypothesis in the Taniguchi and Yamada (2019) framework. In particular, the estimation of the four-factors production function specification reveals that the elasticity of substitution between the robotic capital equipment and skilled labour is lower than the $K_r$-$L_s$ composite and unskilled labour. Additionally, for the six-factors production function, we find that the elasticity of substitution between the robotic capital equipment and high-skilled labour is lower than between the $K_r$-$L_h$ composite and the $K_i$-$L_m$-$L_\ell$ composite. Finally, our findings indicate that the estimated elasticity of substitution between the $K_i$-$L_m$ composite is higher than between ICT capital equipment and low-skilled labour, which implies $\xi > \eta$. In other terms, from the six-factors production function, there is evidence supporting the hypothesis that robotic and ICT capital equipment produce polarising effects. In particular, being able to perform repetitive tasks, industrial robots (and ICT) could substitute middle-qualified workers, in line with the so-called routine biased technical change (see, for instance, Autor *et al.*, 2003; Acemoglu and Autor, 2011; Goos *et al.*, 2014).

## 3.6 Robustness checks

To assess the robustness of findings presented in subsection 3.5.2, we carry out several additional checks. Specifically, we control whether the results are sensitive to a different computation of robotic capital stock. Furthermore, we replicate the benchmark models, by grouping high- and middle skilled labour within the same category.

The first two sets of controls involve a sensitivity analysis of the benchmark results based on the construction of robotic capital using a 5 and 15 percent depreciation rate, respectively, in line with suggestion by Graetz and Michaels (2018).

Tables 3.2 and 3.3 present the estimated elasticities of substitution, where robotic capital is constructed using 5 and 15 percent depreciation rate, respectively. For these two sets, the outcomes uncovered in Table 3.1 of subsection 3.5.2 prove to be robust to the variation of robotic capital depreciation rate, both for the Eden and Gaggl (2018) in WIOD and EU KLEMS samples, and Taniguchi and Yamada (2019) frameworks. In this respect, the results provide additional evidence for the robotic capital-skill complementarity hypothesis. In particular, it is worth noting that the polarising effects of robotic and ICT capital are substantially confirmed within the Taniguchi and Yamada (2019) six-factors production function specification.

The third set of robustness checks replicates the benchmark models, by assessing whether the results are sensitive to a different combination of skill types. Specifically, the skilled category is now obtained by grouping high- and medium-skilled workers, leaving low-skilled ones within the unskilled category. The outcomes of such different labour categorisation are contained in Table 3.4. Once again, the total capital-skill complementarity hypothesis is confirmed when tested on the EU KLEMS sample, whereas the robotic capital turns out to be less substitutable with skilled labour in both the Eden and Gaggl (2018) and Taniguchi and Yamada (2019) frameworks, since in any case we find $1/(1-\rho) < 1/(1-\sigma)$.

**Table 3.2:** Estimated elasticities of substitution (robotic capital $\delta = 5\%$)

| Production functions | $1/(1-\rho)$ | $1/(1-\sigma)$ | $1/(1-\xi)$ | $1/(1-\eta)$ | Obs. |
|---|---|---|---|---|---|
| Eden and Gaggl (2018) WIOD sample (1997-2009) | 2.753 | 3.713 | | | 3468 |
| Eden and Gaggl (2018) EU KLEMS sample (1997-2005) | 10.206 | 17.204 | | | 1344 |
| Taniguchi and Yamada (2019) four factors | 4.346 | 5.561 | | | 485 |
| Taniguchi and Yamada (2019) six factors | 2.010 | 2.268 | 2.479 | 1.026 | 125 |

*Notes*: The estimated coefficients and standard errors are reported in Table C6.2 of the Appendix.

**Table 3.3:** Estimated elasticities of substitution (robotic capital $\delta = 15\%$)

| Production functions | $1/(1-\rho)$ | $1/(1-\sigma)$ | $1/(1-\xi)$ | $1/(1-\eta)$ | Obs. |
|---|---|---|---|---|---|
| Eden and Gaggl (2018) WIOD sample (1997-2009) | 2.525 | 4.951 | | | 3468 |
| Eden and Gaggl (2018) EU KLEMS sample (1997-2005) | 7.181 | 67.678 | | | 1344 |
| Taniguchi and Yamada (2019) four factors | 4.614 | 5.621 | | | 391 |
| Taniguchi and Yamada (2019) six factors | 1.432 | 1.599 | 1.596 | 1.392 | 137 |

*Notes*: The estimated coefficients and standard errors are reported in Table C6.3 of the Appendix.

To sum up, the parametric nonlinear estimation methods provide ample confirmation of the robotic (and ICT) capital-skill complementarity hypothesis.

## 3.7 Does robotic capital produce polarising effects?

One of the outcomes highlighted so far demonstrates that robotic and ICT capital are associated with a polarisation of the wage distribution. In what follows, we

**Table 3.4:** Estimated elasticities of substitution (high- and medium-skilled *vis-à-vis* low-skilled labour)

| Production functions | $1/(1-\rho)$ | $1/(1-\sigma)$ | Obs. |
|---|---|---|---|
| Duffy et al. (2004) WIOD sample (1997-2009) | 0.614 | 0.597 | 6530 |
| Duffy et al. (2004) EU KLEMS sample (1997-2005) | 0.850 | 1.214 | 2026 |
| Eden and Gaggl (2018) WIOD sample (1997-2009) | 4.367 | 32.764 | 3469 |
| Eden and Gaggl (2018) EU KLEMS sample (1997-2005) | 13.185 | 38.189 | 1552 |
| Taniguchi and Yamada (2019) four factors | 9.294 | 18.473 | 587 |

*Notes*: The estimated coefficients and standard errors are reported in Table C6.4 of the Appendix.

check whether only robotic capital produces similar, but independent effects. To this end, we re-estimate the Eden and Gaggl (2018) and the Taniguchi and Yamada (2019) four-factors production function specifications separating middle-skilled from skilled or unskilled workers grouping. Specifically, we consider three different settings. The first one involves high- and medium skilled labour, with robotic capital paired with the former. As for the relationship between medium- and low-skilled workers, we pair robotic capital with the latter,[19] while for the remainder setting, encompassing high- and low-skilled workers, robotic capital is paired with the former. In so doing, the robotic capital-skill complementarity hypothesis is assessed devoting a special attention on the "hollowing out" effects of medium-skilled workers.

Results of these alternative estimated models are presented in Tables 3.5 and 3.6.[20] In particular, our findings indicate the presence of robotic capital-skill

[19]As the null hypothesis of $\sigma \geq 1$ cannot be rejected when robotic capital is paired with medium-skilled labour, being inconsistent with a CES production function formulation, we are required to pair robotic capital with low-skilled labour.

[20]In line with our expectations, the robotic capital-skill complementarity hypothesis is confirmed when tested on high- *vis-à-vis* low-skilled labour, with a lower degree of substitutability between robotic capital high-skilled workers. To save space, these additional results are reported in Tables

complementarity, as the elasticity of substitution between robotic capital and high-skilled labour, $1/(1-\rho)$ is lower than between the $K_r$-$L_h$ composite and medium-skilled labour, $1/(1-\sigma)$, in Table 3.5. Similarly, in Table 3.6, the elasticity of substitution between robotic capital and low-skilled labour, $1/(1-\rho)$, is lower than between the $K_r$-$L_\ell$ composite and medium-skilled labour, $1/(1-\sigma)$.

**Table 3.5:** Estimated elasticities of substitution
(high- *vis-à-vis* medium-skilled labour)

| Production functions | $1/(1-\rho)$ | $1/(1-\sigma)$ | Obs. |
|---|---|---|---|
| Eden and Gaggl (2018) WIOD sample (1997-2009) | 2.645 | 11.737 | 3468 |
| Eden and Gaggl (2018) EU KLEMS sample (1997-2005) | 7.842 | 9.640 | 1344 |
| Taniguchi and Yamada (2019) four factors | 9.294 | 18.473 | 587 |

*Notes*: The estimated coefficients and standard errors are reported in Table C6.5 of the Appendix.

**Table 3.6:** Estimated elasticities of substitution
(medium- *vis-à-vis* low-skilled labour)

| Production functions | $1/(1-\rho)$ | $1/(1-\sigma)$ | Obs. |
|---|---|---|---|
| Eden and Gaggl (2018) WIOD sample (1997-2009) | 3.213 | 48.956 | 3010 |
| Eden and Gaggl (2018) EU KLEMS sample (1997-2005) | 13.622 | 15.615 | 1149 |
| Taniguchi and Yamada (2019) four factors | 3.040 | 5.378 | 823 |

*Notes*: The estimated coefficients and standard errors are reported in Table C6.6 of the Appendix. The robotic capital is paired with low-skilled rather than medium-skilled labour in all settings.

Overall, the polarising effects arising from these results, coupled with those involving ICT capital equipment within the six-factors production function, reinforce

C6.7 and C6.8 of the Appendix.

the view that automation technologies heavily penalise middle-qualified workers. In addition, these outcomes reflect those of de Vries *et al.* (2020), among others, and shed further light on the replaceability of middle-skilled labour with robots.

## 3.8 Concluding remarks

The rising concerns stemming from the intensive use of automation are driving many scholars towards a better understanding of the labour market implications. Furthermore, the pressure exerted by the COVID-19 pandemic for a complete rethinking of the productive process is fuelling a heated debate on whether robots, computerisation and digital technologies will lead either to a job destruction or creation.

In this paper, we participate to the current discussion by investigating the existence of robotic capital-skill complementarity. Specifically, relying upon a constructed measure of robotic capital stock and different frameworks of analysis, we study whether robotic capital is more complementarity to skilled workers - in line, among others, with the so-called "race between technology and education", pioneered by Tinbergen (1974). The empirical analysis is carried out using two distinct samples of countries and industries, mainly based upon the IFR, WIOD and EU KLEMS datasets, over the years 1997-2009 and 1997-2005, respectively. Our main findings consistently point to a lower elasticity of substitution between robotic capital and skilled labour. Additionally, we find evidence of polarising effects produced by robotic and ICT capital, with results that turn out to be robust both with respect to a different computation of robotic capital stock and workers grouping.

In terms of policy implications, the robotic (plus ICT) capital-skill complementarity suggests measures aimed at improving productivity, wage and education differentials for lower-skilled labour. As our findings highlight, middle-skilled workers might be the most hit by automation technologies, insofar as robots will become increasingly important in the production process and able to reproduce even more complex tasks. By and large, policymakers face numerous challenges. In the short run, the focus should be placed in new organisational needs of production, exceedingly influenced by the ongoing COVID-19 pandemic. Moreover, the advent of improved robots as well as new technological developments, typically incorporated in intangible assets, such as those related to the artificial intelligence, may dramatically impact workers in the medium- and long-run.

Overall, our study casts additional light on understanding the mechanisms underlying the current forces operating in the labour markets, especially in manufacturing industries of advanced and transition economies. If on the one hand industrial robots, as a subset of the broader category of automation technologies, turn out to be a powerful engine of economic growth, on the other hand they appear to be associated with intensifying inequalities.

# Appendix Chapter 1

## A Additional Tables

**Table A.1:** List of countries included in the analysis

| | |
|---|---|
| Advanced countries | Australia, Austria, Belgium, Canada, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Iceland, Ireland, Israel, Italy, Japan, Latvia, Lithuania, Luxembourg, Malta, Netherlands, New Zealand, Norway, Portugal, Singapore, Slovakia, Slovenia, Spain, Sweden, Switzerland, United Kingdom, United States |
| Emerging countries | Albania, Algeria, Angola, Argentina, Armenia, Bahamas, Barbados, Botswana, Brazil, Bulgaria, Cameroon, Chile, China, Colombia, Costa Rica, Croatia, Dominica, Dominican Republic, Ecuador, Egypt, El Salvador, Fiji, Grenada, Guatemala, Hungary, India, Indonesia, Jamaica, Jordan, Kazakhstan, Lesotho, Malaysia, Mauritius, Mexico, Mongolia, Morocco, Nigeria, Pakistan, Panama, Paraguay, Peru, Philippines, Poland, Senegal, Serbia, Seychelles, South Africa, Sri Lanka, Suriname, Swaziland, Thailand, Trinidad and Tobago, Tunisia, Turkey, Uruguay, Yemen, Zambia |

*Notes*: Economies are defined as Advanced or Emerging following the World Economic Outlook classification (IMF, 2016).

**Table A.2:** Data sources and coverage

| Variable | Source | Time span | Countries |
|---|---|---|---|
| Gini Coefficient | Standardized World Inequality Database (SWIID), v7.1, August 2018, Solt (2016) | 1970-2014 | 90 |
| Economic Globalisation Index | KOF Index of Globalisation, Gygli *et al.* (2019) | 1970-2015 | 90 |
| Energy Use | World Development Indicators, World Bank | 1970-2014 | 90 |
| Relative Price of Investment Goods | Penn World Tables 9.0, Feenstra *et al.* (2015) | 1970-2014 | 90 |
| Air Transport | World Development Indicators, World Bank | 1970-2014 | 88 |
| Mobile Cellular Subscriptions | World Development Indicators, World Bank | 1980-2014 | 88 |
| Financial Sector Development | Financial Development and Structure Dataset, July 2018, Beck *et al.* (2000) | 1970-2015 | 90 |
| Real GDP per-capita | Penn World Tables 9.0, Feenstra *et al.* (2015) | 1970-2014 | 90 |
| Inflation (annual %) | World Development Indicators, World Bank | 1970-2015 | 90 |
| Human Capital Index | Penn World Tables 9.0, Feenstra *et al.* (2015) | 1970-2014 | 85 |
| Bureaucracy Quality | International Country Risk Guide, The PRS Group (2017) | 1984-2015 | 82 |
| Rate of Change of Urban Agglomerations | World Urbanization Prospects 2018, United Nations (2018) | 1970-2015 | 78 |

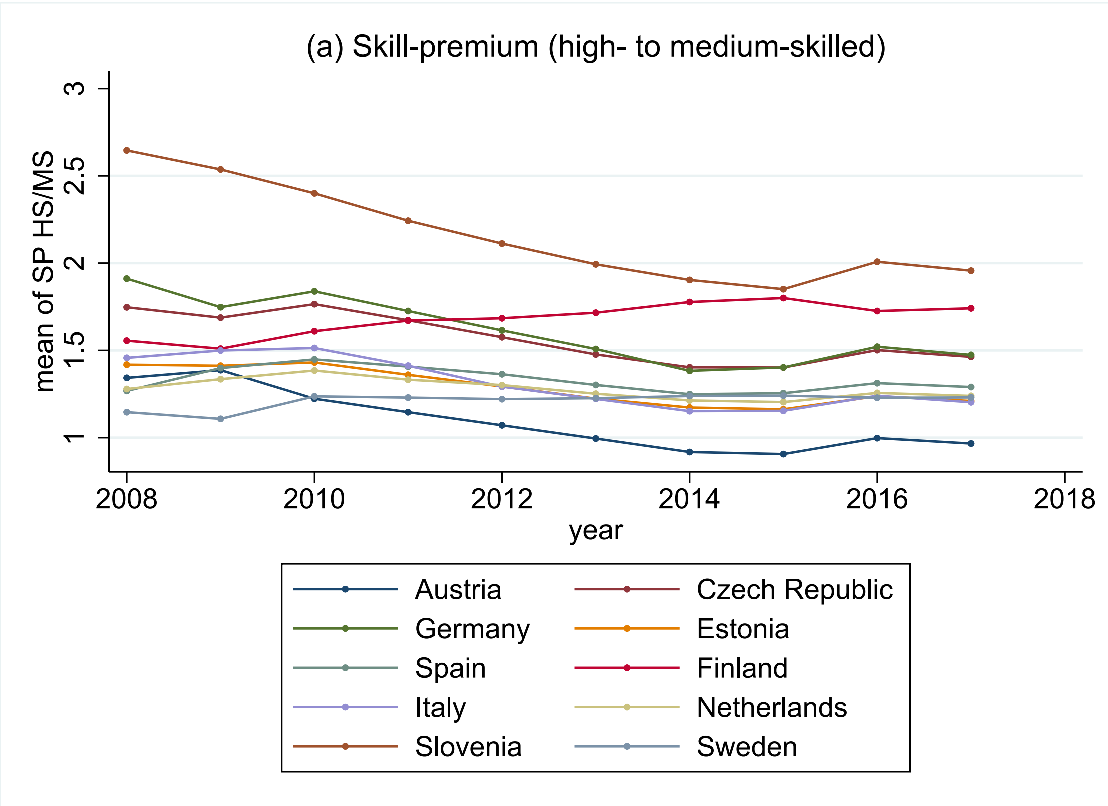
**Table A.3:** Fixed-effects regression results:
Dependent variable is Gini Coefficient

| | Model v1 | | Model v2 | | Model v3 | |
|---|---|---|---|---|---|---|
| | Linear | Nonlinear | Linear | Nonlinear | Linear | Nonlinear |
| Economic Globalisation Index | 0.0112 | -0.1042 | 0.0207 | -0.0639*** | 0.0081 | -0.0925 |
| | (0.0135) | (0.0627) | (0.0132) | (0.0637) | (0.0149) | (0.0654) |
| (Economic Globalisation Index)$^2$ | | 0.0010* | | 0.007 | | 0.0009 |
| | | (0.005) | | (0.005) | | (0.0006) |
| Energy Use | -0.0659 | 0.5656 | | | | |
| | (0.1798) | (0.3625) | | | | |
| (Energy Use)$^2$ | | -0.0458* | | | | |
| | | (0.0265) | | | | |
| Air Transport | | | -0.0004 | -0.0012 | | |
| | | | (0.0005) | (0.0034) | | |
| (Air Transport)$^2$ | | | | 0.0000 | | |
| | | | | (0.0000) | | |
| Mobile Cellular Subscriptions | | | | | 0.0043 | -0.0107 |
| | | | | | (0.0052) | (0.0096) |
| (Mobile Cellular Subscriptions))$^2$ | | | | | | 0.001 |
| | | | | | | (0.0001) |
| Relative Price of Investment Goods | 0.1405 | -0.2098 | 0.0547 | 0.7785 | 0.0248 | 0.3973 |
| | (0.5746) | (2.0017) | (0.5730) | (2.1035) | (0.5556) | (1.9349) |
| (Relative Price of Investment Goods)$^2$ | | 0.1108 | | -0.5499 | | -0.2572 |
| | | (1.2237) | | (1.2525) | | (1.1598) |
| Financial Sector Development | 0.0029 | 0.0071 | 0.0019 | 0.0108 | 0.0030 | 0.0104 |
| | (0.0042) | (0.0080) | (0.0049) | (0.0091) | (0.0043) | (0.0092) |
| (Financial Sector Development)$^2$ | | -0.0000 | | -0.0000 | | -0.0000 |
| | | (0.0000) | | (0.0000) | | (0.0000) |
| Real GDP per-capita | -0.0049 | -0.0775* | -0.0068 | -0.0385 | -0.0228 | -0.0318 |
| | (0.0361) | (0.0396) | (0.0346) | (0.0390) | (0.0330) | (0.0359) |
| (Real GDP per-capita)$^2$ | 0.0005 | 0.0011** | 0.0005 | 0.0008* | 0.0006 | 0.0006 |
| | (0.0004) | (0.0004) | (0.0004) | (0.0004) | (0.0003) | (0.0004) |
| Constant | 9.9793*** | 11.5292*** | 9.7199*** | 11.1168*** | 10.3067*** | 12.2573*** |
| | (2.4418) | (2.8510) | (2.3791) | (2.9030) | (2.2455) | (2.9211) |
| No. Observations | 349 | 349 | 343 | 343 | 352 | 352 |
| R-squared (within) | 0.6720 | 0.6869 | 0.6769 | 0.6837 | 0.6693 | 0.6972 |
| Time effects | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes*: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. Estimates are based on dynamic panel data fixed-effects estimation, using data averaged over five-years periods, three lags of the dependent variable and the other regressors lagged one period.

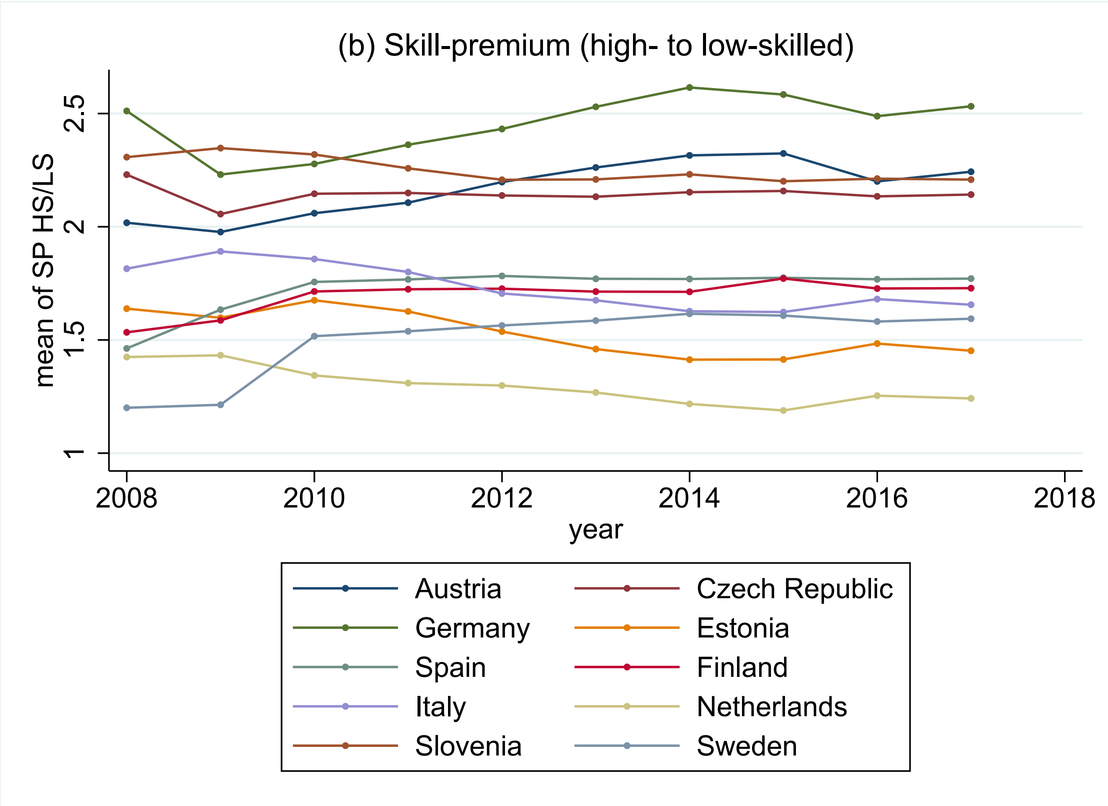
# B Additional Figures and Tables

Figure B.1: Developments in the skill-premium of high to medium skilled workers, 2008-2017



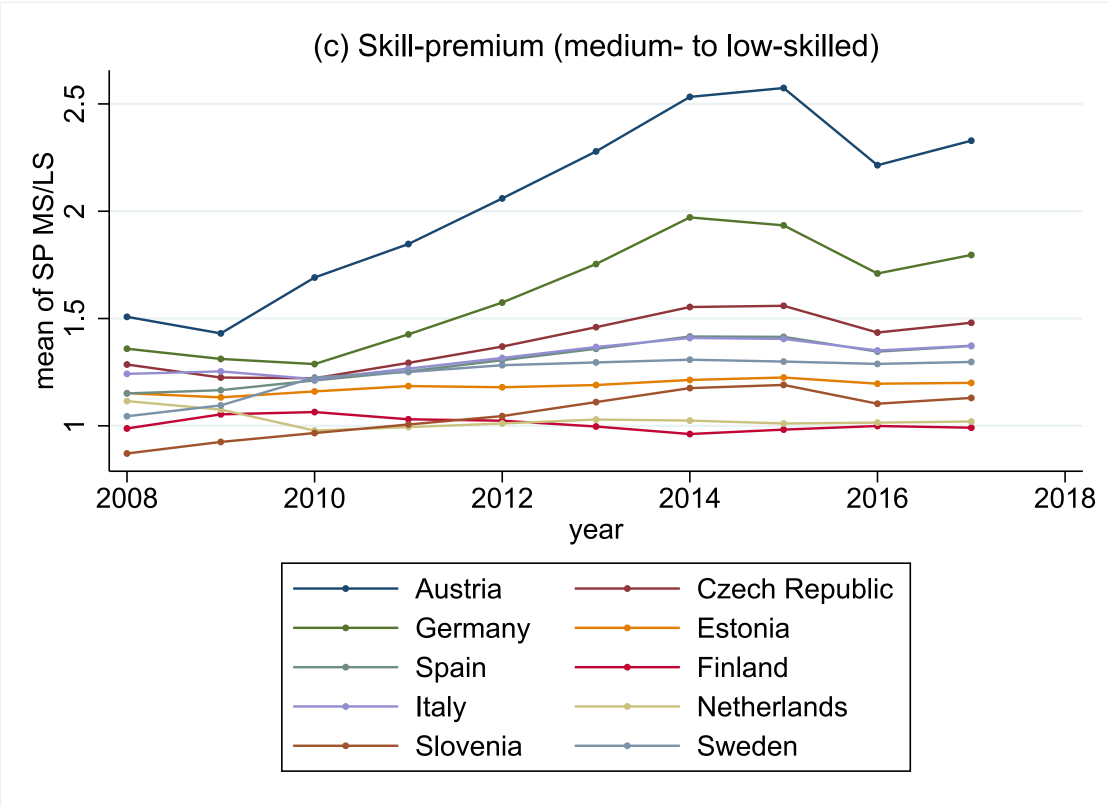

*Notes*: Skill-premium between high- and medium-skilled workers evolution, for a subsample of European countries. The figure reports mean values over the period 2008-2017 using 2008 sectoral employments weights to aggregate to the country level

Figure B.2: Developments in the skill-premium of high to low skilled workers, 2008-2017




*Notes*: Skill-premium between high- and low-skilled workers evolution, for a subsample of European countries. The figure reports mean values over the period 2008-2017 using 2008 sectoral employments weights to aggregate to the country level

Figure B.3: Developments in the skill-premium of medium to low skilled workers, 2008-2017




*Notes*: Skill-premium between medium- and low-skilled workers evolution, for a subsample of European countries. The figure reports mean values over the period 2008-2017 using 2008 sectoral employments weights to aggregate to the country level

**Table B.1a:** Summary Statistics: Levels Averaged by Country

| Country | HS/MS | HS/LS | MS/LS | ROB | ICT | R&D | S&DB | N_ICT | Y | RS HS/MS | RS HS/LS | RS MS/LS |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Austria | 1.176 | 2.272 | 1.99 | 1.81 | .02 | .283 | .034 | 2.801 | 44882.34 | .613 | 3.045 | 4.126 |
| Belgium | 1.515 | 1.596 | 1.051 | 2.197 | .003 | .247 | .018 | 1.617 | 46955.48 | 2.131 | 3.899 | 1.83 |
| Czech Republic | 1.66 | 2.084 | 1.278 | 1.326 | .014 | .116 | .014 | 2.884 | 51291.51 | .289 | 4.65 | 14.978 |
| Denmark | 1.525 | 2.595 | 1.758 | 7.312 | .012 | .305 | .025 | 1.502 | 508000 | .671 | 3.713 | 4.785 |
| Estonia | 1.224 | 1.656 | 1.372 | 3.431 | .011 | .377 | .033 | 2.076 | 22188.34 | 1.021 | 2.367 | 2.137 |
| Finland | 1.349 | 1.609 | 1.199 | .036 | .086 | .031 | .011 | 2.281 | 2380.545 | .764 | 6.42 | 5.957 |
| France | 1.343 | 1.722 | 1.285 | 2.44 | .044 | .123 | .018 | 1.846 | 122000 | 2.886 | 2.406 | .534 |
| Germany | 1.668 | 1.678 | 1.008 | 3.157 | .035 | .31 | .022 | 1.519 | 28000.54 | .976 | 5.646 | 4.007 |
| Greece | 1.492 | 1.761 | 1.191 | 2.642 | .019 | .178 | .06 | 1.009 | 178000 | 1.084 | 2.833 | 2.341 |
| Italy | 1.567 | 1.96 | 1.25 | 1.054 | .005 | .08 | .031 | 2.193 | 139000 | .803 | 1.278 | 1.494 |
| Japan | 1.349 | 1.934 | 1.454 | .055 | .036 | .057 | .007 | 1.59 | 14760.1 | 1.623 | 5.242 | 1.369 |
| Lithuania | 1.368 | 1.738 | 1.284 | 3.5 | .008 | .097 | .027 | 1.911 | 203000 | .352 | 1.232 | 1.618 |
| Netherlands | 2.17 | 1.537 | .841 | 8.207 | .005 | .102 | .026 | .247 | 761000 | .589 | 25.435 | 21.802 |
| Slovak Republic | 2.005 | 3.035 | 1.522 | .011 | .026 | .164 | .164 | 2.04 | 5295.929 | .742 | 10.136 | 10.861 |
| Slovenia | 1.229 | 1.189 | .992 | 1.196 | .002 | .242 | .055 | 1.579 | 59905.51 | 1.22 | 3.663 | 1.891 |
| Spain | 1.187 | 1.444 | 1.215 | 3.752 | .057 | .31 | .044 | 1.522 | 46326.65 | .882 | 4.212 | 4.13 |
| Sweden | 2.185 | 2.294 | 1.064 | 1.124 | .004 | .121 | .012 | 2.314 | 6800.225 | .516 | 2.907 | 4.19 |
| United Kingdom | 1.356 | 1.91 | 1.455 | 1.477 | .006 | .072 | .014 | 3.149 | 21217.77 | .346 | 5.25 | 19.887 |
| Unweighted mean | 1.492 | 1.873 | 1.306 | 0.97 | 0.03 | 0.123 | 0.032 | 3.244 | 55760 | 0.931 | 5.361 | 5.562 |

*Notes*: HS/MS: ratio of high to medium skilled wages; HS/LS: ratio of high to low skilled wages; MS/LS: ratio of medium to low skilled wages; ROB: Robot Density; ICT: ratio of real ICT capital stock net of Software & Databases to real gross value added; R&D: ratio of R&D capital stock to real gross value added; S&DB: ratio of Software & Databases capital stock to real gross value added; N_ICT: ratio of real non-ICT capital stock to real gross value added; Y: real gross value added; RS HS/MS: relative supply of high-skilled to medium skilled; RS HS/LS: relative supply of high-skilled to low-skilled; RS MS/LS: relative supply of medium-skilled to low-skilled. The table reports mean values over the period 2008-2017 using 2008 sectoral employments weights to aggregate to the country level. parentheses.

**Table B.1b:** Summary Statistics: Levels Averaged by Industry

| Industry | HS/MS | HS/LS | MS/LS | ROB | ICT | R&D | S&DB | N_ICT | Y | RS HS/MS | RS HS/LS | RS MS/LS |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Agriculture, forestry and fishing | 1.77 | 2.077 | 1.352 | 0.05 | 0.02 | 0.013 | 0.009 | 3.918 | 18078.5 | 0.221 | 0.524 | 3.899 |
| Mining and quarrying | 1.483 | 1.976 | 1.365 | 0.28 | 0.05 | 0.05 | 0.018 | 3.892 | 3824.9 | 0.431 | 1.444 | 5.93 |
| Total Manufacturing | 1.542 | 1.926 | 1.272 | 5.46 | 0.03 | 0.257 | 0.037 | 1.446 | 225000 | 0.412 | 1.672 | 6.036 |
| Electricity, gas, steam; water supply, sewerage, waste management | 1.407 | 1.763 | 1.28 | 0.02 | 0.09 | 0.034 | 0.049 | 7.68 | 21624.5 | 0.6 | 2.286 | 5.015 |
| Construction | 1.418 | 1.771 | 1.266 | 0.04 | 0.01 | 0.008 | 0.013 | 1.211 | 44511.2 | 0.306 | 1.105 | 4.97 |
| Education | 1.426 | 1.872 | 1.344 | 0.13 | 0.01 | 0.324 | 0.056 | 1.618 | 39486.7 | 3.49 | 19.911 | 7.494 |

*Notes*: HS/MS: ratio of high to medium skilled wages; HS/LS: ratio of high to low skilled wages; MS/LS: ratio of medium to low skilled wages; ROB: Robot Density; ICT: ratio of real ICT capital stock net of Software & Databases to real gross value added; R&D: ratio of R&D capital stock to real gross value added; S&DB: ratio of Software & Databases capital stock to real gross value added; N_ICT: ratio of real non-ICT capital stock to real gross value added; Y: real gross value added; RS HS/MS: relative supply of high-skilled to medium skilled; RS HS/LS: relative supply of high-skilled to low-skilled; RS MS/LS: relative supply of medium-skilled to low-skilled. The table reports mean values over the period 2008-2017 using 2008 sectoral employments weights to aggregate to the country level.

**Table B.2a:** Summary Statistics: Levels Averaged by Country

| Country | GLOB | FFD_DVA | DFD_FVA | EPL_PERM | EPL_TEMP |
|---|---|---|---|---|---|
| Austria | 1.553 | 0.385 | 0.349 | 289.883 | 14.182 |
| Belgium | 2.73 | 0.37 | 0.444 | 462.623 | 23.114 |
| Czech Republic | 2.373 | 0.481 | 0.382 | 195.167 | 10.992 |
| Denmark | 1.501 | 0.357 | 0.285 | 259.423 | 13.428 |
| Estonia | 2.213 | 0.414 | 0.464 | 253.257 | 11.219 |
| Finland | 1.396 | 0.342 | 0.278 | 141.057 | 20.619 |
| France | 1.077 | 0.253 | 0.339 | 279.413 | 62.39 |
| Germany | 1.451 | 0.362 | 0.295 | 314.96 | 13.611 |
| Greece | 0.7 | 0.2 | 0.375 | 265.762 | 44.678 |
| Italy | 1.116 | 0.274 | 0.259 | 333.555 | 33.596 |
| Japan | 0.52 | 0.168 | 0.263 | - | - |
| Lithuania | 1.597 | 0.312 | 0.373 | 272.244 | 12.89 |
| Netherlands | 2.252 | 0.314 | 0.232 | 256.211 | 15.202 |
| Slovak Republic | 2.812 | 0.499 | 0.463 | 333.591 | 10.395 |
| Slovenia | 1.872 | 0.466 | 0.438 | 283.266 | 28.075 |
| Spain | 0.931 | 0.229 | 0.288 | 250.469 | 84.677 |
| Sweden | 1.222 | 0.32 | 0.251 | 219.809 | 9.812 |
| United Kingdom | 0.8 | 0.201 | 0.318 | 265.09 | 2.304 |
| Unweighted mean | 1.092 | 0.318 | 1.997 | 273.569 | 26.434 |

*Notes*: GLOB: sum of imports plus export to real gross value added; FFD_DVA: ratio of real domestic value added embodied in foreign final demand to real gross value added; DFD_FVA: ratio of real foreign value added embodied in domestic final demand to real gross value added; EPL_PERM: EPL permanent employees; EPL_TEMP: EPL temporary employees. The table reports means weighted by 2008 share of each country's employment.

**Table B.2b:** Summary Statistics: Levels Averaged by Industry

| Industry | GLOB | FFD_DVA | DFD_FVA | EPL_PERM | EPL_TEMP |
|---|---|---|---|---|---|
| Agriculture, forestry and fishing | 0.853 | 0.369 | 0.463 | 234.56 | 50.4 |
| Mining and quarrying | 1.065 | 0.583 | 6.516 | 261.6 | 15.905 |
| Total Manufacturing | 3.051 | 0.59 | 0.506 | 288.83 | 15.604 |
| Electricity, gas, steam; water supply, sewerage, waste management | 0.801 | 0.257 | 0.229 | 291.62 | 19.551 |
| Construction | 0.421 | 0.059 | 0.039 | 271.3 | 28.318 |
| Education | 0.059 | 0.036 | 0.036 | 271.72 | 27.528 |

*Notes*: GLOB: sum of imports plus export to real gross value added; FFD_DVA: ratio of real domestic value added embodied in foreign final demand to real gross value added; DFD_FVA: ratio of real foreign value added embodied in domestic final demand to real gross value added; EPL_PERM: EPL permanent employees; EPL_TEMP: EPL temporary employees. The table reports means weighted by 2008 share of each country's employment.

# APPENDIX CHAPTER 3

## C1 The measurement of the robotic capital stock

The robotic capital measure employed throughout the analysis is built upon two variables: the stock of industrial robots and their price.

As for the robot stock variable construction, the procedure largely follows that proposed by Graetz and Michaels (2018), which we refer to for more detailed information.

Data on average unit price of robots are retrieved from the IFR reports. This is computed as the ratio of the turnover of total robot systems to the number of robots delivered in a specific country. The IFR provides a series of average unit price of robots (in current, thousand dollars) for a small group of countries.[21] Specifically, robot prices are available for Japan, United States, Germany, Rep. of Korea, United Kingdom and France, from 1998 to 2008; whereas, for Italy, robot prices are available from 1998 to 2006. Therefore, the 2007 and 2008 Italy's robot price observations are computed using the average robot price growth rate for countries for which we have original prices data.

At this point, the main necessary assumption we need to impute the average unit price of robots for the remaining countries (in both the WIOD and EU KLEMS samples) relies upon the geographical, economic proximity. In particular:

- European countries take on average robot prices of Germany, United Kingdom, France and Italy;
- American countries take on robot prices for the United States;

[21] See, for instance, IFR (2015).

- Asian countries (plus Australia) take on average prices of Japan and Rep. of Korea.

In order to obtain robot prices data for the years 1997 and 2009, the series are smoothed by employing uniformly weighted moving averages, with 1 lagged term, 1 forward term and the current observation in the filter.[22]

The robotic capital stock, $K_r$, is calculated by multiplying the number of industrial robots, $R^S$, by their price, $R^P$, and converted in real terms applying the country-sector specific capital deflator, $D$:

$$K_{r,cit} = \frac{R^S_{cit} * R^P_{ct}}{D_{cit}} \tag{AC1.1}$$

Finally, the constructed robotic capital measure in (AC1.1) is expressed in real PPP 2005 adjusted international dollars using the PPP conversion factor from Inklaar and Timmer (2014).

[22] The specified procedure is only applied to the WIOD sample. As for the EU KLEMS sample, whose series ends in 2005, only the observation referring to 1997 is computed.

# C2 Countries and industries

## C2.1 List of countries

**Table C2.1a:** List of EU KLEMS countries

| Code | Country |
|---|---|
| AUS | Australia |
| AUT | Austria |
| CZE | Czech Republic |
| DEU | Germany |
| DNK | Denmark |
| ESP | Spain |
| FIN | Finland |
| GBR | United Kingdom |
| ITA | Italy |
| JPN | Japan |
| KOR | Korea, Republic of |
| NLD | Nederlands |
| SVN | Slovenia |
| SWE | Sweden |
| USA | Unted States |

**Table C2.1b:** List of WIOD countries

| Code | Country |
|---|---|
| AUS | Australia |
| AUT | Austria |
| BEL | Belgium |
| BGR | Bulgaria |
| BRA | Brazil |
| CHN | China |
| CZE | Czech Republic |
| DEU | Germany |
| DNK | Denmark |
| ESP | Spain |
| EST | Estonia |
| FIN | Finland |
| FRA | France |
| GBR | United Kingdom |
| GRC | Greece |
| HUN | Hungary |
| IDN | Indonesia |
| IND | India |
| IRL | Ireland |
| ITA | Italy |
| JPN | Japan |
| KOR | Korea, Republic of |
| LTU | Lithuania |
| LVA | Latvia |
| MLT | Malta |
| NLD | Nederlands |
| POL | Poland |
| PRT | Portugal |
| ROU | Romania |
| RUS | Russian Federation |
| SVK | Slovakia |
| SVN | Slovenia |
| SWE | Sweden |
| TUR | Turkey |
| USA | Unted States |

## C2.2 List of industries

**Table C2.2:** List of WIOD and EU KLEMS industries

| Code | Label | Description |
|---|---|---|
| AtB | Agriculture | Agriculture, hunting, forestry, and fishing |
| C | Mining | Mining and quarrying |
| 15t16 | Food products | Food, beverages and tobacco |
| 17t19 | Textiles | Textiles, textile products, leather and footwear |
| 20 | Wood products | Wood and products of wood and cork |
| 21t22 | Paper | Pulp, paper, paper products, printing and publishing |
| 23 | Fuel | Coke, refined petroleum and nuclear fuel |
| 24 | Chemical | Chemicals and chemical products |
| 25 | Rubber and plastics | Rubber and plastics |
| 26 | Other Mineral | Other non-metallic mineral |
| 27t28 | Metal | Basic metals and fabricated metal |
| 29 | Machinery | Machinery, nec |
| 30t33 | Electronics | Electrical and optical equipment |
| 34t35 | Transport equipment | Transport equipment |
| E | Utilities | Electricity, gas and water supply |
| F | Construction | Construction |
| M | Education, R&D | Education |

*Notes*: Industries codes are ISIC Rev. 3.1.

# C3 Descriptive statistics and figures

**Table C3.1a:** Main variables' average by Country

| Country | Stock of Robots | Robotic capital on Employment | Non-Robotic capital on Employment | Relative wages | Value added | No. of Observations |
|---|---|---|---|---|---|---|
| AUS | 49.194 | .032 | 312.643 | 1.472 | 10665.39 | 221 |
| AUT | 135.514 | .203 | 224.719 | .965 | 4968.097 | 187 |
| BEL | 218.453 | .277 | 286.907 | 1.192 | 5776.465 | 221 |
| BGR | .753 | 0 | 1.067 | 9.492 | 34.949 | 221 |
| BRA | 81.412 | .01 | 81.607 | 5.333 | 14833.36 | 221 |
| CHN | 413.073 | .003 | 32.716 | 2.154 | 202000 | 176 |
| CZE | 55.261 | .043 | 88.723 | 1.081 | 2300.788 | 187 |
| DEU | 3815.895 | .362 | 159.017 | 1.088 | 47447.34 | 187 |
| DNK | 74.374 | .267 | 519.885 | .899 | 2932.206 | 187 |
| ESP | 661.609 | .159 | 194.235 | 2.935 | 16724.53 | 187 |
| EST | .07 | .001 | 45.862 | .889 | 187.426 | 221 |
| FIN | 99.914 | .165 | 207.297 | .999 | 3981.137 | 187 |
| FRA | 925.024 | .195 | 185.895 | 1.319 | 28342.99 | 187 |
| GBR | 493.797 | .111 | 269.49 | 1.312 | 28266.44 | 187 |
| GRC | 2.929 | .007 | 133.015 | 1.934 | 2915.361 | 221 |
| HUN | 13.81 | .014 | 54.272 | 1.548 | 1394.426 | 187 |
| IDN | 5.294 | 0 | 18.734 | 5.253 | 7467.281 | 218 |
| IND | 29.997 | .002 | 48.865 | 2.504 | 47905.12 | 221 |
| IRL | 2.078 | .009 | 170.927 | 1.114 | 2937.723 | 176 |
| ITA | 1421.785 | .382 | 224.148 | 2.274 | 25532.24 | 187 |
| JPN | 15316.05 | .757 | 614.343 | .85 | 113000 | 136 |
| KOR | 1711.027 | .115 | 230.552 | .905 | 23053.55 | 221 |
| LTU | .087 | .001 | 207.072 | .939 | 1993.468 | 221 |
| LVA | .058 | 0 | 27.84 | 1.074 | 191.972 | 217 |
| MLT | .075 | .004 | 99.63 | 9.574 | 119.272 | 208 |
| NLD | 87.017 | .117 | 358.706 | 1.297 | 7716.577 | 187 |
| POL | 33.867 | .011 | 47.317 | 1.109 | 5559.832 | 187 |
| PRT | 48.702 | .105 | 156.591 | 9.795 | 2946.01 | 204 |
| ROU | 2.004 | 0 | 2.725 | 9.492 | 227.133 | 221 |
| RUS | 442.659 | .014 | 9.606 | 1.223 | 5231.068 | 221 |
| SVK | 28.007 | .05 | 96.576 | .979 | 1185.767 | 221 |
| SVN | 19.607 | .079 | 99.404 | 1.385 | 550.493 | 221 |
| SWE | 266.835 | .23 | 236.976 | 1.003 | 7740.69 | 187 |
| TUR | 18.851 | 0 | 8.63 | 5.164 | 934.479 | 221 |
| USA | 3820.161 | .237 | 472.04 | 1.042 | 178000 | 221 |

*Source*: Authors' calculations based on IFR (2019) and WIOD (2015).

**Table C3.1b:** Main variables' average by Industry

| Industry | Stock of Robots | Robotic capital on Employment | Non-Robotic capital on Employment | Relative wages | Value added | No. of Observations |
|---|---|---|---|---|---|---|
| 15t16 | 332.964 | .056 | 86.02 | 2.501 | 21291.93 | 419 |
| 17t19 | 28.861 | .035 | 79.783 | 2.505 | 9561.105 | 408 |
| 20 | 180.313 | .099 | 60.313 | 2.449 | 4233.705 | 419 |
| 21t22 | 43.91 | .007 | 77.538 | 2.36 | 13156.9 | 419 |
| 23 | 1.588 | .006 | 520.063 | 2.205 | 8964.896 | 391 |
| 24 | 70.173 | .014 | 154.523 | 2.415 | 20987.09 | 419 |
| 25 | 525.356 | .194 | 72.129 | 2.357 | 8299.853 | 419 |
| 26 | 112.622 | .054 | 125.151 | 2.525 | 10017.17 | 419 |
| 27t28 | 1009.696 | .142 | 74.653 | 2.373 | 26205.92 | 419 |
| 29 | 419.679 | .065 | 62.308 | 2.352 | 19818.4 | 419 |
| 30t33 | 3096.73 | .221 | 89.563 | 2.341 | 52152.49 | 419 |
| 34t35 | 6237.008 | .825 | 81.308 | 2.333 | 20760.24 | 419 |
| AtB | 9.41 | .002 | 108.774 | 7.908 | 46588.5 | 419 |
| C | 2.771 | .022 | 462.474 | 2.722 | 14276.38 | 419 |
| E | 4.227 | .001 | 669.795 | 1.461 | 20964.41 | 419 |
| F | 18.477 | .001 | 22.317 | 3.63 | 44498.41 | 419 |
| M | 77.031 | .003 | 35.94 | 1.385 | 23804.89 | 416 |

*Source*: Authors' calculations based on IFR (2019) and WIOD (2015).

**Table C3.2a:** Main variables' average by Country

| Country | Stock of Robots | Robotic capital on Employment | Non-Robotic capital on Employment | Relative wages | Value added | No. of Observations |
|---|---|---|---|---|---|---|
| AUS | 36.738 | .02 | 263.927 | 1.46 | 9499.119 | 144 |
| AUT | 79.042 | .113 | 208.189 | 1.19 | 4890.001 | 144 |
| CZE | 16.352 | .016 | 79.289 | 1.233 | 1960.941 | 144 |
| DEU | 3599.891 | .324 | 149.469 | 1.291 | 43719.8 | 153 |
| DNK | 78.5 | .253 | 458.663 | 1.122 | 3179.924 | 117 |
| ESP | 595.295 | .146 | 180.096 | 2.55 | 15770.36 | 153 |
| FIN | 89.881 | .142 | 189.932 | 1.144 | 3512.483 | 153 |
| GBR | 483.698 | .104 | 283.359 | 1.048 | 26299.28 | 153 |
| ITA | 1333.169 | .336 | 209.925 | .558 | 24149.35 | 153 |
| JPN | 14915.85 | .796 | 443.446 | .89 | 99435.32 | 153 |
| KOR | 863.364 | .052 | 222.957 | .922 | 18759.8 | 144 |
| NLD | 66.855 | .079 | 343.929 | .998 | 7404.92 | 144 |
| SWE | 307.412 | .242 | 215.863 | 1.068 | 7087.255 | 126 |
| USA | 1526.454 | .093 | 448.248 | 1.031 | 184000 | 144 |

*Source*: Authors' calculations based on IFR (2019) and EU KLEMS (2009).

**Table C3.2b:** Main variables' average by Industry

| Industry | Stock of Robots | Robotic capital on Employment | Non-Robotic capital on Employment | Relative wages | Value added | No. of Observations |
|---|---|---|---|---|---|---|
| 15t16 | 712.42 | .089 | 103.224 | 1.344 | 28801.23 | 126 |
| 17t19 | 79.282 | .075 | 105.799 | 1.447 | 16139.89 | 126 |
| 20 | 745.3 | .308 | 80.683 | 1.182 | 6223.214 | 126 |
| 21t22 | 127.417 | .015 | 92.664 | 1.073 | 24783.49 | 126 |
| 23 | 2.743 | .006 | 620.746 | 1.113 | 9545.882 | 108 |
| 24 | 136.019 | .017 | 220.235 | 1.114 | 32478.37 | 108 |
| 25 | 560.356 | .227 | 89.728 | 1.14 | 13191.92 | 108 |
| 26 | 322.231 | .101 | 148.262 | 1.169 | 14919.1 | 126 |
| 27t28 | 2514.342 | .302 | 107.856 | 1.138 | 40169.13 | 126 |
| 29 | 1460.283 | .148 | 89.389 | 1.056 | 35111.35 | 126 |
| 30t33 | 10298.69 | .585 | 118.331 | 1.055 | 101000 | 126 |
| 34t35 | 23458.62 | 2.483 | 156.872 | 1.039 | 39347.11 | 63 |
| AtB | 22.009 | .003 | 184.29 | 1.839 | 38323.32 | 126 |
| C | 6.113 | .054 | 937.168 | 1.209 | 14774.32 | 126 |
| E | 13.031 | .003 | 1273.802 | .938 | 32862.54 | 126 |
| F | 34.372 | .001 | 24.171 | 1.203 | 65892.25 | 126 |
| M | 196.491 | .007 | 58.544 | .947 | 41510.61 | 126 |

*Source*: Authors' calculations based on IFR (2019) and EU KLEMS (2009).

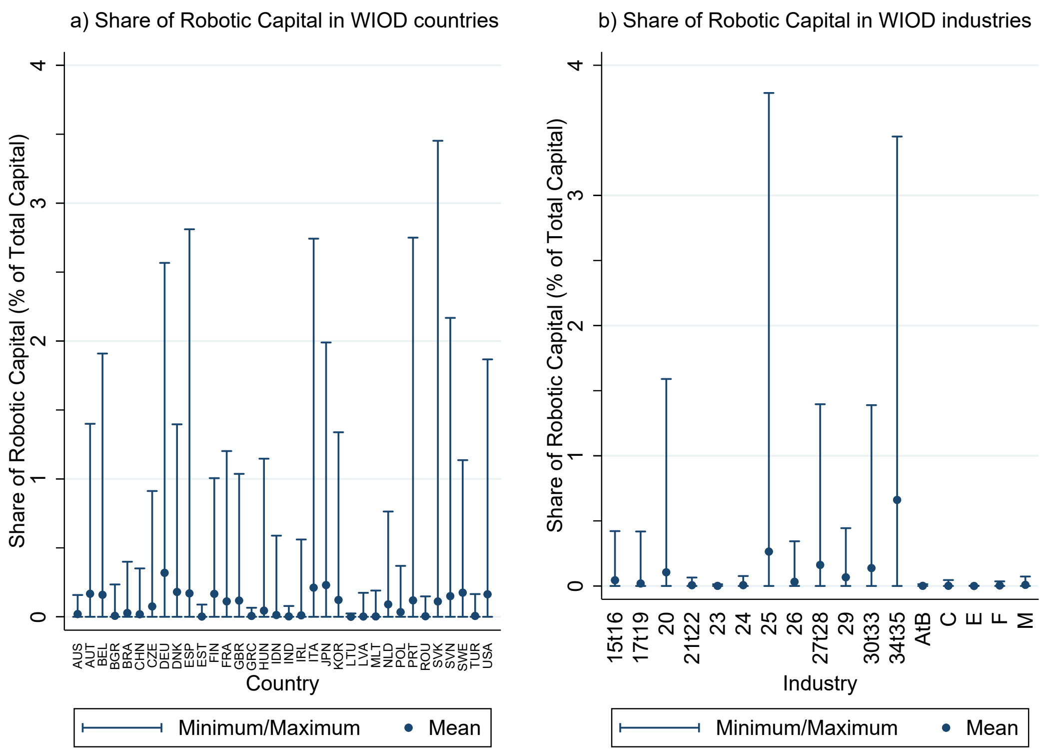



Figure C3.1: Share of robotic capital
in WIOD countries and industries, 1997-2009

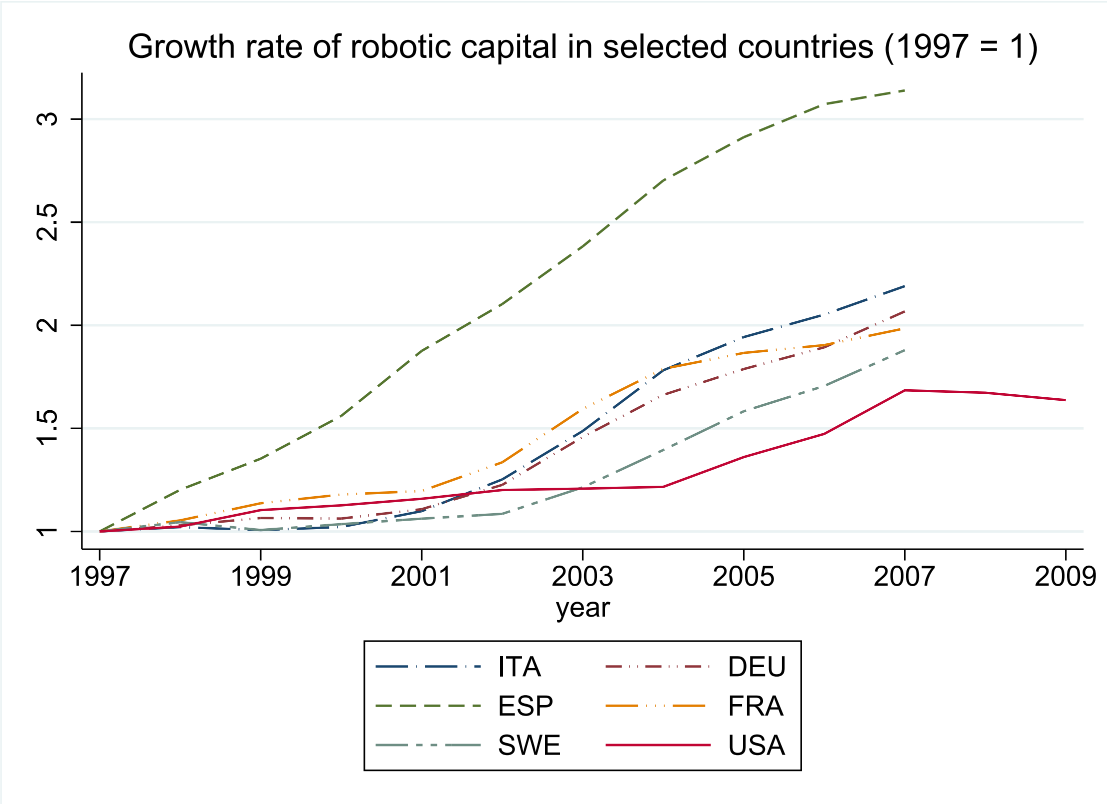



Figure C3.2: Robotic capital evolution
in selected WIOD countries, 1997-2009

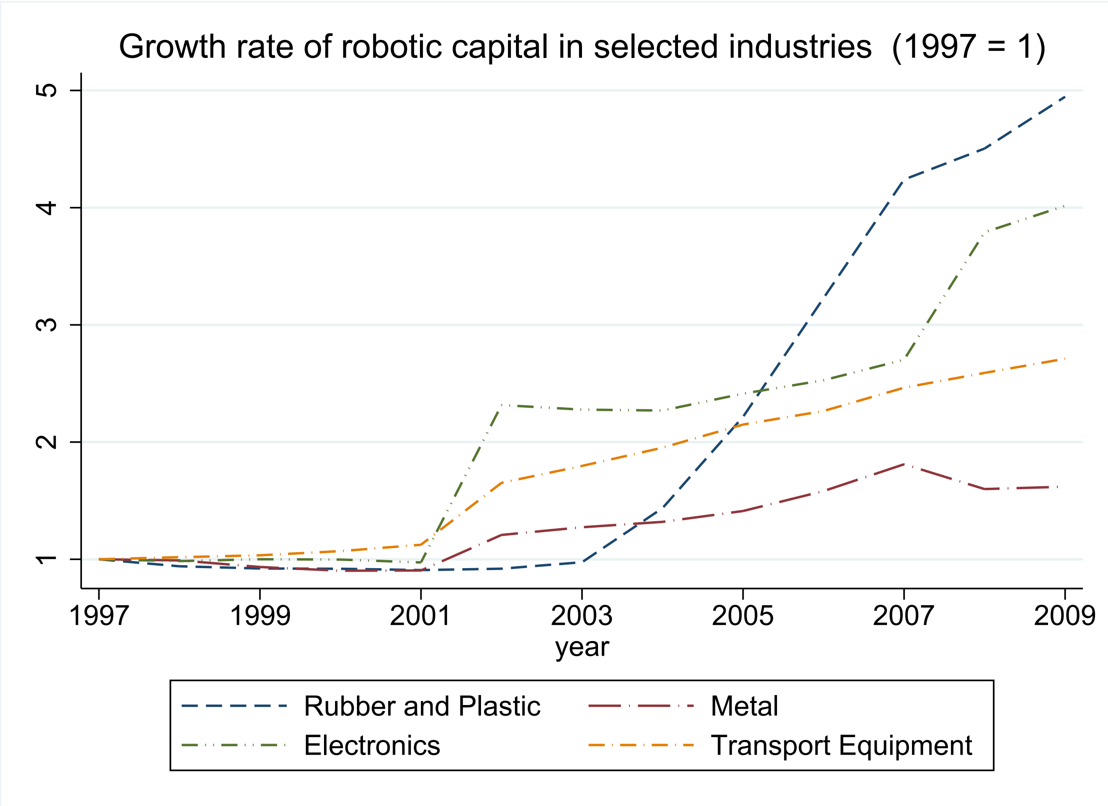



Figure C3.3: Robotic capital evolution
in selected WIOD industries, 1997-2009

## C4 Derivation of the Eden and Gaggl (2018) specification

In the spirit of the Eden and Gaggl (2018) procedure, we consider a Cobb-Douglas production function with non-robotic capital, $K_{nr}$, and a composite input, $Q$, consisting of robotic capital equipment, $K_r$, and the shares of hours worked by skilled ($L_s^s$) and unskilled ($L_u^s$) labour. Therefore, the production function takes the form:

$$Y = K_{nr}^{\alpha} Q^{1-\alpha} \tag{AC4.1}$$

The composite input, $Q$, is defined by the following nested CES aggregator:

$$Q = \left[\beta(L_u^s)^{\sigma} + (1-\beta)Z^{\sigma}\right]^{\frac{1}{\sigma}} \tag{AC4.2}$$

with $Z$ specified as:

$$Z = \left[\gamma K_r^{\rho} + (1-\gamma)(L_s^s)^{\rho}\right]^{\frac{1}{\rho}} \tag{AC4.3}$$

where $\beta$ and $\gamma$ represent distribution parameters, while $\sigma$, $\rho \leq 1$ are parameters governing the degree of substitution between input factors.

By assuming competitive factor markets and that firms are wages and rental prices takers, the first-order conditions entails a relationship in terms of (the logs of) income shares and relative quantities, as follows:

$$\ln\left(\frac{sK_r}{sL_s}\right) = \ln\left(\frac{\gamma}{1-\gamma}\right) + \rho \ln\left(\frac{K_r}{L_s^s}\right) \tag{AC4.4}$$

$$\ln\left(\frac{sL_u}{sZ}\right) = \ln\left(\frac{\beta}{1-\beta}\right) + \sigma \ln\left(\frac{L_u^s}{Z}\right) \tag{AC4.5}$$

where $sK_r$, $sL_s$, $sL_u$, $sZ$ denote the income shares of $K_r$, $L_s^s$, $L_u^s$ and $Z$, respectively. By adding the two error terms in equation (AC4.4) and (AC4.5), and subscripts for country, industry and time, we obtain the estimated models in equations (3.6) and (3.7).

# C5 Derivation of the Taniguchi and Yamada (2019) specification

Building on the contributions of Krusell *et al.* (2000) and Caselli and Coleman (2002), the production functions proposed by Taniguchi and Yamada (2019), in their four- and six-factors versions, make use of multiple nested CES aggregators. The following subsections present the four- and six-factors specifications, as adapted to our needs.

## C5.1 Four-factors production function

In the four-factors production function, we consider a Cobb-Douglas, with a nested CES aggregator, where output, $Y$, is obtained using a combination of neutral, non-robotic capital, $K_{nr}$, robotic capital, $K_r$, and hours worked by skilled and unskilled labour, $L_s$ and $L_u$, respectively, expressed as:

$$Y = AK_{nr}^{\alpha}\left\{\beta\left[\gamma K_r^{\rho}+(1-\gamma)L_s^{\rho}\right]^{\frac{\sigma}{\rho}}+(1-\beta)L_u^{\sigma}\right\}^{\frac{1-\alpha}{\sigma}} \tag{AC5.1}$$

where $A$ is a Hicks-neutral efficiency parameter; $\alpha$, $\beta$ and $\gamma$ represent distribution parameters; $\rho < 1$ is the parameter governing the elasticity of substitution between robotic-capital, $K_r$, and skilled labour, $L_s$, while $\sigma < 1$ is the parameter governing the elasticity of substitution between $K_r$-$L_s$ composite and unskilled labour, $L_u$.

Firms deviating from the profit-maximising behaviour in competitive markets have to equate marginal productivities to marginal costs, s.t.:

$$w_s = \omega_s \frac{\partial Y}{\partial L_s} \tag{AC5.2}$$

$$w_u = \omega_u \frac{\partial Y}{\partial L_u} \tag{AC5.3}$$

$$r_{nr} = \omega_{nr} \frac{\partial Y}{\partial K_{nr}} \tag{AC5.4}$$

$$r_r = \omega_r \frac{\partial Y}{\partial K_r} \tag{AC5.5}$$

where $\omega_j$, with $j = \{s, u, nr, r\}$, indicates the wedge, namely the deviation from profit-maximising behaviour; $w_s$ and $w_u$ indicate the hourly wages of skilled and unskilled labour, respectively, whereas $r_{nr}$ and $r_r$ denote the rental prices of non-robotic and robotic capital, respectively.

The ratio of first-order conditions in equations (AC5.2) and (AC5.3) determines the relationship between the (log of) skilled to unskilled relative wage and the (logs of) relative quantities and complementarity effect:

$$\ln\left(\frac{w_s}{w_u}\right) = \underbrace{-(1-\sigma)\ln\left(\frac{L_s}{L_u}\right)}_{\text{quantity effect}} + \underbrace{\frac{\sigma-\rho}{\rho}\ln\left[\left(\frac{K_r}{L_s}\right)^{\rho}+1\right]}_{\text{complementarity effect}} + \ln\left(\frac{\omega_s}{\omega_u}\right) \tag{AC5.6}$$

Additionally, the ratio of first-order conditions in equations (AC5.2) and (AC5.5) shapes the relationship between the (log of) skilled wage to the rental price of robotic capital ratio and the (log of) skilled labour to robotic capital ratio:

$$\ln\left(\frac{w_s}{r_r}\right) = -(1-\rho)\ln\left(\frac{L_s}{K_r}\right) + \ln\left(\frac{\omega_s}{\omega_r}\right) \tag{AC5.7}$$

Finally, by taking first-differences of equation (AC5.6) and (AC5.7), we derive the estimated models presented in (3.8) and (3.9), if we assume that the wedges, $\omega_j$, represent time invariant country-sector specific effects.

## C5.2 Six-factors production function

The six-factors production function is characterised by output, $Y$, obtained using a combination of ICT, robotic and other capital ($K_i$, $K_r$ and $K_o$), and hours worked by high-, medium- and low-skilled labour, ($L_h$, $L_m$ and $L_\ell$), as follows:

$$Y = AK_o^{\alpha}\left\{\beta\left[\gamma K_r^{\rho}+(1-\gamma)L_h^{\rho}\right]^{\frac{\sigma}{\rho}} + (1-\beta)\left[\delta\left[\zeta K_i^{\eta}+(1-\zeta)L_\ell^{\eta}\right]^{\frac{\xi}{\eta}}+(1-\delta)L_m^{\xi}\right]^{\frac{\sigma}{\xi}}\right\}^{\frac{1-\alpha}{\sigma}} \tag{AC5.8}$$

where $A$ is a Hicks-neutral efficiency parameter; $\alpha$, $\beta$, $\gamma$, $\delta$ and $\zeta$ are distribution parameters; $\sigma$, $\rho$, $\eta$, $\xi < 1$ are, respectively, the parameters governing the elasticity of substitution between the $K_r$-$L_h$ composite and the $K_i$-$L_m$-$L_\ell$ composite, $K_r$ and $L_h$, the $K_i$-$L_\ell$ composite and $L_m$, and $K_i$ and $L_\ell$.

Firms deviating from the profit-maximising behaviour in competitive markets have to equate marginal productivities to marginal costs, which implies:

$$w_h = \omega_h \frac{\partial Y}{\partial L_h} \tag{AC5.9}$$

$$w_m = \omega_m \frac{\partial Y}{\partial L_m} \tag{AC5.10}$$

$$w_\ell = \omega_l \frac{\partial Y}{\partial L_\ell} \tag{AC5.11}$$

$$r_o = \omega_o \frac{\partial Y}{\partial K_o} \tag{AC5.12}$$

$$r_i = \omega_i \frac{\partial Y}{\partial K_i} \tag{AC5.13}$$

$$r_r = \omega_r \frac{\partial Y}{\partial K_r} \tag{AC5.14}$$

where $\omega_j$, with $j = \{h, m, \ell, o, i, r\}$, indicates the wedge, namely the deviation from profit-maximising behaviour; $w_h$, $w_m$ and $w_\ell$ indicate the hourly wages of high-, medium- and low-skilled labour, respectively, whereas $r_i$, $r_r$ and $r_o$ denote the rental prices of ICT, robotic and other capital, respectively.

The ratio of first-order conditions in equations (AC5.9) and (AC5.10) determines the relationship between the (log of) high- to medium-skilled relative wage and the (logs of) relative quantities and complementarity effect:

$$\ln\left(\frac{w_h}{w_m}\right) = \underbrace{-(1-\sigma)\ln\left(\frac{L_h}{L_m}\right)}_{\text{quantity effect}}$$
$$\underbrace{+\frac{\sigma-\rho}{\rho}\ln\left[\left(\frac{K_r}{L_h}\right)^{\rho}+1\right]-\frac{\sigma-\xi}{\xi}\ln\left[\left(\frac{K_i}{L_m}\right)^{\eta}+\left(\frac{L_\ell}{L_m}\right)^{\eta}+1\right]}_{\text{complementarity effect}}+\ln\left(\frac{\omega_h}{\omega_m}\right) \tag{AC5.15}$$

Likewise, the ratio of first-order conditions in equations (AC5.10) and (AC5.11) determines the relationship between the (log of) medium- to low-skilled relative wage and the (logs of) relative quantities and complementarity effect:

$$\ln\left(\frac{w_m}{w_\ell}\right) = \underbrace{-(1-\xi)\ln\left(\frac{L_m}{L_l}\right)}_{\text{quantity effect}} + \underbrace{\frac{\eta-\xi}{\eta}\ln\left[\left(\frac{K_i}{L_\ell}\right)^{\eta}+1\right]}_{\text{complementarity effect}} + \ln\left(\frac{\omega_m}{\omega_\ell}\right) \tag{AC5.16}$$

Furthermore, the ratio of first-order conditions in equations (AC5.9) and (AC5.14) entails the (logs of) high-skilled labour wage and rental price of robotic capital, implying that:

$$\ln\left(\frac{w_h}{r_r}\right) = -(1-\rho)\ln\left(\frac{L_h}{K_r}\right) + \ln\left(\frac{\omega_h}{\omega_r}\right) \tag{AC5.17}$$

Finally, the ratio of first-order conditions in equation (AC5.11) and (AC5.13) involves the (logs of) low-skilled labour wage and the rental price of ICT capital, as follows:

$$\ln\left(\frac{w_\ell}{r_i}\right) = -(1-\eta)\ln\left(\frac{L_\ell}{K_i}\right) + \ln\left(\frac{\omega_\ell}{\omega_i}\right) \tag{AC5.18}$$

The derivation of the estimated model presented in (3.10)-(3.13) is obtained by taking first-differences of equations (AC5.15)-(AC5.18) to remove the wedges, $\omega_j$, assumed as time invariant country-sector specific effects.

## C5.3 The rental price of capital

Let assume that the production function of a representative firm is given by:

$$Y_t = f(K_t^{'}, L_t^{'}; A_t) \tag{AC5.19}$$

where $Y$ represents the output, $K^{'}$ and $L^{'}$ denote the vectors of capital and labour inputs at time $t$, respectively, s.t. $K^{'} = (K_{1t}, K_{2t}, ..., K_{jt}, ..., K_{nt})$ and $L^{'} = (L_{1t}, L_{2t}, ..., L_{jt}, ..., L_{nt})$.

By denoting $I$ as the investment, $p$ as its price and the discount factor as $\beta = 1/(1+i)$, with $i$ as an interest rate, the Bellman equation of the firm can be expressed as:

$$V(K_t) = \max_{K_{j,t+1}, L_{jt}, I_{jt}} \left\{ Y_t - \sum_{j=1}^{J_K} p_{jt} I_{jt} - \sum_{j=1}^{J_L} w_{jt} L_{jt} + \beta_{t+1} \mathbb{E}_t [V(K_{t+1})] \right\} \tag{AC5.20}$$

subject to the general law of capital motion:

$$K_{j,t+1} = (1 - \delta_j) K_{jt} + I_{jt} \tag{AC5.21}$$

where $\delta$ is the depreciation rate.

The first-order condition of (AC5.20) with respect to the capital, $K_{j,t+1}$, yields:

$$p_{jt} = \beta_{t+1} \mathbb{E}_t \left[ \frac{\partial V_{t+1}}{\partial K_{j,t+1}} \right] \tag{AC5.22}$$

By applying the envelop theorem, we get:

$$\frac{\partial V_t}{\partial K_{jt}} = \frac{\partial f_t}{\partial K_{jt}} + (1 - \delta_j) \tag{AC5.23}$$

If the decision of a firm deviating from the profit-maximising behaviour takes place assuming $A_{t+1}$ and $p_{j,t+1}$ as known, then the first-order condition with respect to the capital can be represent as follows:

$$\frac{\partial f_{t+1}}{\partial K_{j,t+1}} = i_{t+1} p_{jt} + \delta_j p_{j,t+1} - (p_{j,t+1} - p_{j,t}) \equiv \omega_r r_{j,t+1} \tag{AC5.24}$$

where $r$ and $\omega_r$ denote, respectively, the rental price of capital and wedge.

The interest rate, $i$, is derived according to the procedure proposed by O'Mahony and Timmer (2009) and represents the internal rate of return (IRR) of capital:

$$i_{jt} = \frac{r_{jt}K_{jt} - \sum_j \delta_j p_{jt}K_{jt} + \sum_j \left(p_{jt} - p_{j,t-1}\right)K_{jt}}{\sum_j p_{j,t-1}K_{jt}}, \tag{AC5.25}$$

where $r_t K_t = \sum_j r_j K_j$ for $j = \{nr, r\}$ in the four-factors production function and for $j = \{o, i, r\}$ in the six-factors production function.

Finally, the first-order condition with respect to the labour simply yields:

$$\frac{\partial f_t}{\partial L_j} = \omega_j w_{jt} \tag{AC5.26}$$

where $w_j$ and $\omega_j$ indicate, respectively, the $j_{th}$-wage group and wedges.

The depreciation rate, $\delta$, is computed as a weighted average of depreciation rates of non-robotic, ICT and other capital components, whereas it is equal to 0.1 in the case of robotic capital.[23]

[23] In the robustness checks involving the two alternative computations of the robotic capital stock, the depreciation rates take on values of 0.05 and 0.15, respectively.

# C6 Parametric estimation results

**Table C6.1:** Benchmark NLLS and GMM parameter estimates

| | Duffy et. al (2004) WIOD | Duffy et al. (2004) EU KLEMS | Eden and Gaggl (2018) WIOD | Eden and Gaggl (2018) EU KLEMS | Taniguchi and Yamada (2019) 4-Factors | Taniguchi and Yamada (2019) 6-Factors |
|---|---|---|---|---|---|---|
| $\rho$ | -0.667*** | -0.473** | 0.622*** | 0.891*** | 0.840*** | 0.123* |
| | (0.075) | (0.206) | (0.013) | (0.016) | (0.081) | (0.076) |
| $\sigma$ | -0.793*** | -0.157* | 0.758*** | 0.964*** | 0.869*** | 0.562*** |
| | (0.189) | (0.086) | (0.013) | (0.022) | (0.060) | (0.109) |
| $\xi$ | | | | | | 0.249** |
| | | | | | | (0.099) |
| $\eta$ | | | | | | 0.161* |
| | | | | | | (0.092) |
| $\beta$ | 0.997*** | 0.845*** | 0.392*** | 0.312*** | | |
| | (0.002) | (0.052) | (0.006) | (0.010) | | |
| $\gamma$ | 0.996*** | 0.995*** | 0.219*** | 0.285*** | | |
| | (0.001) | (0.006) | (0.007) | (0.011) | | |
| Adj $R^2$ | 0.899 | 0.884 | | | | |
| Obs. | 6426 | 1872 | 3468 | 1344 | 431 | 147 |

*Notes*: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. Duffy *et al.* (2004) production function, in equation (3.5), estimated using NLLS estimation method and White's heteroskedasticity correction. Production functions by Eden and Gaggl (2018), in equations (3.6)-(3.7), and Taniguchi and Yamada (2019), in equations (3.8)-(3.9) and (3.10)-(3.13), simultaneously estimated using GMM estimation techniques, with lagged values of input factors as instrumental variables and HAC robust standard errors.

**Table C6.2:** Robustness checks: GMM parameter estimates (robotic capital $\delta = 5\%$)

| | Eden and Gaggl (2018) WIOD | Eden and Gaggl (2018) EU KLEMS | Taniguchi and Yamada (2019) 4-Factors | Taniguchi and Yamada (2019) 6-Factors |
|---|---|---|---|---|
| $\rho$ | 0.636*** | 0.902*** | 0.770*** | 0.502** |
| | (0.013) | (0.016) | (0.081) | (0.104) |
| $\sigma$ | 0.730*** | 0.941*** | 0.820*** | 0.559*** |
| | (0.012) | (0.022) | (0.089) | (0.104) |
| $\xi$ | | | | 0.596*** |
| | | | | (0.084) |
| $\eta$ | | | | 0.480*** |
| | | | | (0.123) |
| $\beta$ | 0.399*** | 0.321*** | | |
| | (0.006) | (0.010) | | |
| $\gamma$ | 0.241*** | 0.292*** | | |
| | (0.007) | (0.011) | | |
| Obs. | 3468 | 1344 | 485 | 125 |

*Notes*: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. Production functions by Eden and Gaggl (2018), in equations (3.6)-(3.7), and Taniguchi and Yamada (2019), in equations (3.8)-(3.9) and (3.10)-(3.13), simultaneously estimated using GMM estimation techniques, with lagged values of input factors as instrumental variables and HAC robust standard errors.

**Table C6.3:** Robustness checks: GMM parameter estimates (robotic capital $\delta = 15\%$)

| | Eden and Gaggl (2018) WIOD | Eden and Gaggl (2018) EU KLEMS | Taniguchi and Yamada (2019) 4-Factors | Taniguchi and Yamada (2019) 6-Factors |
|---|---|---|---|---|
| $\rho$ | 0.603*** | 0.860*** | 0.783*** | 0.301** |
| | (0.014) | (0.017) | (0.047) | (0.117) |
| $\sigma$ | 0.985*** | 0.941*** | 0.822*** | 0.374*** |
| | (0.013) | (0.021) | (0.047) | (0.090) |
| $\xi$ | | | | 0.373*** |
| | | | | (0.073) |
| $\eta$ | | | | 0.282** |
| | | | | (0.085) |
| $\beta$ | 0.306*** | 0.321*** | | |
| | (0.006) | (0.010) | | |
| $\gamma$ | 0.268*** | 0.292*** | | |
| | (0.007) | (0.011) | | |
| Obs. | 3468 | 1344 | 391 | 137 |

*Notes*: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. Production functions by Eden and Gaggl (2018), in equations (3.6)-(3.7), and Taniguchi and Yamada (2019), in equations (3.8)-(3.9) and (3.10)-(3.13), simultaneously estimated using GMM estimation techniques, with lagged values of input factors as instrumental variables and HAC robust standard errors.

**Table C6.4:** Robustness checks: NLLS and GMM parameter estimates (high- and medium-skilled *vis-à-vis* low-skilled labour)

| | Duffy et. al (2004) WIOD | Duffy et al. (2004) EU KLEMS | Eden and Gaggl (2018) WIOD | Eden and Gaggl (2018) EU KLEMS | Taniguchi and Yamada (2019) 4-Factors |
|---|---|---|---|---|---|
| $\rho$ | -0.626*** | -0.175** | 0.771*** | 0.924*** | 0.892*** |
| | (0.082) | (0.206) | (0.014) | (0.015) | (0.082) |
| $\sigma$ | -0.674*** | 0.176* | 0.969*** | 0.973*** | 0.945*** |
| | (0.095) | (0.086) | (0.007) | (0.015) | (0.064) |
| $\beta$ | 0.990*** | 0.852*** | 0.331*** | 0.297*** | |
| | (0.001) | (0.052) | (0.003) | (0.009) | |
| $\gamma$ | 0.997*** | 0.791*** | 0.202*** | 0.285*** | |
| | (0.002) | (0.006) | (0.010) | (0.014) | |
| Adj $R^2$ | 0.992 | 0.902 | | | |
| Obs. | 6530 | 2026 | 3469 | 1552 | 587 |

*Notes*: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. Duffy *et al.* (2004) production function, in equation (3.5), estimated using NLLS estimation method and White's heteroskedasticity correction. Production functions by Eden and Gaggl (2018), in equations (3.6)-(3.7), and Taniguchi and Yamada (2019), in equations (3.8)-(3.9), simultaneously estimated using GMM estimation techniques, with lagged values of input factors as instrumental variables and HAC robust standard errors.

**Table C6.5:** Robustness checks: GMM parameter estimates (high- *vis-à-vis* medium-skilled labour)

| | Eden and Gaggl (2018) WIOD | Eden and Gaggl (2018) EU KLEMS | Taniguchi and Yamada (2019) 4-Factors |
|---|---|---|---|
| $\rho$ | 0.622*** | 0.872*** | 0.892*** |
| | (0.013) | (0.019) | (0.082) |
| $\sigma$ | 0.836*** | 0.933*** | 0.945*** |
| | (0.012) | (0.022) | (0.064) |
| $\beta$ | 0.330*** | 0.360*** | |
| | (0.004) | (0.008) | |
| $\gamma$ | 0.199*** | 0.195*** | |
| | (0.007) | (0.010) | |
| Obs. | 3468 | 1344 | 587 |

*Notes*: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. Production functions by Eden and Gaggl (2018), in equations (3.6)-(3.7), and Taniguchi and Yamada (2019), in equations (3.8)-(3.9) simultaneously estimated using GMM estimation techniques, with lagged values of input factors as instrumental variables and HAC robust standard errors.

**Table C6.6:** Robustness checks: GMM parameter estimates (medium- *vis-à-vis* low-skilled labour)

| | Eden and Gaggl (2018) WIOD | Eden and Gaggl (2018) EU KLEMS | Taniguchi and Yamada (2019) 4-Factors |
|---|---|---|---|
| $\rho$ | 0.688*** | 0.926*** | 0.671*** |
| | (0.011) | (0.018) | (0.091) |
| $\sigma$ | 0.979*** | 0.935*** | 0.814*** |
| | (0.007) | (0.026) | (0.053) |
| $\beta$ | 0.431*** | 0.461*** | |
| | (0.004) | (0.011) | |
| $\gamma$ | 0.325*** | 0.343*** | |
| | (0.010) | (0.016) | |
| Obs. | 3010 | 1149 | 823 |

*Notes*: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. Production functions by Eden and Gaggl (2018), in equations (3.6)-(3.7), and Taniguchi and Yamada (2019), in equations (3.8)-(3.9) simultaneously estimated using GMM estimation techniques, with lagged values of input factors as instrumental variables and HAC robust standard errors.

**Table C6.7:** Estimated elasticities of substitution (high- *vis-à-vis* low-skilled labour)

| Production functions | $1/(1-\rho)$ | $1/(1-\sigma)$ | Obs. |
|---|---|---|---|
| Eden and Gaggl (2018) WIOD sample (1997-2009) | 2.161 | 13.465 | 3471 |
| Eden and Gaggl (2018) EU KLEMS sample (1997-2005) | 7.853 | 15.035 | 1344 |
| Taniguchi and Yamada (2019) four factors | 2.765 | 4.614 | 587 |

*Notes*: The estimated coefficients and standard errors are reported in Table C6.8.

**Table C6.8:** Robustness checks: GMM parameter estimates (high- *vis-à-vis* low-skilled labour)

| | Eden and Gaggl (2018) WIOD | Eden and Gaggl (2018) EU KLEMS | Taniguchi and Yamada (2019) 4-Factors |
|---|---|---|---|
| $\rho$ | 0.537*** | 0.872*** | 0.638*** |
| | (0.013) | (0.018) | (0.097) |
| $\sigma$ | 0.925*** | 0.933*** | 0.783*** |
| | (0.010) | (0.017) | (0.057) |
| $\beta$ | 0.281*** | 0.275*** | |
| | (0.002) | (0.004) | |
| $\gamma$ | 0.168*** | 0.201*** | |
| | (0.006) | (0.011) | |
| Obs. | 3471 | 1344 | 587 |

*Notes*: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses. Production functions by Eden and Gaggl (2018), in equations (3.6)-(3.7), and Taniguchi and Yamada (2019), in equations (3.8)-(3.9) simultaneously estimated using GMM estimation techniques, with lagged values of input factors as instrumental variables and HAC robust standard errors.

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