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THE COMPLEMENTARITY OF HUMAN AND ORGANIZATIONAL CAPITAL TO THE PRODUCTIVITY OF ROBOTS

Yifeng (Philip) Chen
(University of Cambridge)

Chander Velu
(University of Cambridge)

Duncan McFarlane
(University of Cambridge)

ABSTRACT

We investigate the effect of intangible capital and robot adoption on labor productivity in 18 European Union countries between 1995 and 2015. Previous studies show that both robot adoption and intangible capital enhance productivity. However, little is known about how intangible capital may influence the impact of robot adoption on productivity. We find that intangible capital, notably human and organizational capital, displays complementarity with robots and hence moderates the effect on productivity. Human capital investment reduces the effect of robots on productivity in the short term but enhances it in the long term. By contrast, investments in organizational capital increase the effect of robots on productivity in the short term but reduce it in the long term. The contrasting dynamics are based on whether the complementarity with robots is direct, as in human capital, or indirect and systems-based, as in organizational capital. Pickering's Mangle of Practice provides a conceptual framework to understand the formation of complementarity over time. Our findings point to the importance of to considering the development of new organizational structures and business models following the adoption of robots in order to obtain the benefits of productivity growth.

Keywords: Robots; Intangible Capital; Human Capital; Organizational Capital; Tuning; Business Models

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INTRODUCTION

The increasing use of industrial robots in the economy has been shown to substantially raise productivity (Graetz and Michael 2018). However, despite the widespread use of robots, productivity growth in many advanced economies continues to lag (Crafts 2018). One possible explanation is the growth of intangible capital at the expense of tangible assets, which have hitherto been de-emphasized in conventional accounting methods (Brynjolfsson et al. 2018). Like robot usage, intangible capital greatly enhances productivity (Marrocu et al. 2011, Corrado et al. 2012,). Current studies have begun to explore productivity gains from the complementarity between technological and intangible capital, predominantly in the context of information and communications technology (ICT) but the dynamics of how this relationship unfolds over time have not been explicated (Bresnahan et al. 2002). In particular, little is known about how intangible capital influences the impact of robot adoption on productivity. Our study contributes to a deeper understanding of such a relationship by examining the complementarity of robots and intangible capital.

In this article, we factor in the moderating effects of intangible capital on robots as they pertain to labor productivity.[1] In order to understand this interactive relationship between robots and intangible capital, we refer to theories developed in the complementarity literature (Teece 1986, Adegbesan 2009, Brynjolfsson and Milgrom 2013), as well as to Pickering's (1993, 1995) *Mangle of Practice*, which offers a conceptual framework to understand the dynamics of complementarity.

[1] For the purpose of this article, we examine labor productivity (see Graetz and Michael 2018, İmrohoroğlu and Tüzel 2014). Henceforth, unless otherwise stated, productivity in this article refers specifically to labor productivity, defined as output per worker.

This is important because existing studies tend to treat assets as either complementary or not, without entertaining if and how they *become* complements.[2]

In particular, we explore the role of human and organizational capital in increasing robots' productivity-enhancing potential. Both types of intangible capital are widely accepted as critical for economic performance (Black and Lynch 1996, Crespi et al. 2007). We develop our hypotheses based on firm level dynamics. Although the data we use for our analysis is collected at the firm level, the reporting is at the country-industry level. As such, we employ a two-pronged empirical strategy to mitigate the data aggregation issue and identify the effect of intangible capital on robot productivity. First, we use national and industrial level data to test our main hypotheses. Second, we attempt to account for firm level interaction effects by using instrumental variables to capture such industry competitive dynamics. We demonstrate that even after accounting for firm level interaction effects our main hypotheses hold. Our results show that robots indeed contribute to productivity, as does intangible capital, which is consistent with previous studies. In addition, we find that human and organizational capital moderates the effect of robots on productivity. This moderating effect differs depending on whether we consider the short or long term: human capital investment reduces the effect of robots on productivity in the short term but enhances it in the long term; investments in organizational capital increase the effect of robots on productivity in the short term but reduce it in the long term. Such an observation may be caused by the difference in the nature of human capital vis-à-vis organizational capital. Pickering's *Mangle of Practice* provides the theoretical foundations for why this may be the case. Human capital predominantly affects the quality of the labor force; hence, its complementarity with robots is likely to be direct and bi-

[2] Love et al. (2014) and Brynjolfsson and McElheran (2019) had alluded to the influence of time but did not explicitly discuss the development of complementarity over time.

directional. By contrast, organizational capital affects the firm's organizational structure and business model, developing systems-based (or multi-directional) and indirect complementarity which affects multiple firm components. Our findings have implications for organizational structure and business model innovation in firms wishing to fully reap the potential productivity improvement from robot adoption.

This article offers three main contributions. First, recent studies have highlighted that often new technologies are introduced to improve productivity which might not materialize without organizational changes (Sergeeva et al. 2020). We contribute to this literature stream with a nuanced understanding of the relationship between intangible capital and the effect of robots on productivity in the short and long term. In doing so, we provide a possible explanation for the slowdown in productivity growth that has been observed recently in major economies. Second, we contribute to the complementarity literature by showing the dynamics of the evolution of complementarity between new technology and intangible capital over time. Third, we contribute to the business model literature by showing how organizational capital investments influence productivity following the adoption of new technologies.

The article proceeds as follows. Section 2 summarizes the current literature on the productivity gains brought about by robot adoption, intangible capital investment, and the formation of complementarity. In Section 3 we develop the hypotheses. In Section 4 we describe the data to test the hypotheses and the econometric methodology used to estimate quantitative relationships. Section 5 reports the results of the empirical analysis and how it supports the hypotheses. Section 6 discusses the implications of our findings, and we conclude in Section 7.

LITERATURE REVIEW

The adoption of robots has generally been shown to increase productivity at the industry sector level across countries, as well as at firm level. Graetz and Michael (2018) is perhaps the most comprehensive aggregate study in this area to-date, covering 14 industrial sectors in 17 countries over a decade. In an earlier study Kromann et al. (2011) employed a similar set of data and methods. Both studies find a positive association between robots and long-run productivity. Several other aggregate studies also report substantial productivity gains from robot adoption (Acemoglu and Restrepo 2018, Salomons 2018).

The rapid development of software/programming capabilities, computing power, and other technological innovations in recent decades has vastly improved the usefulness of robots and widened their applicability. Robots have become virtually indispensable for certain high-end manufacturing industries such as automobiles and electronics. They are also deployed in hazardous environments, such as smelting and chemical engineering plants while increasingly permeating industries that were not traditionally heavy users of robotics such as agriculture (Reddy et al. 2016, Bechar and Vigeault 2017), though large-scale deployment remains challenging due to the agricultural environment being highly unstructured and heterogenous. In service settings such as in medicine, automated systems are used to reduce error rates (Aron et al. 2011).

A number of studies have emphasized the role of human capital, and the training and skills necessary to fully benefit from robot adoption (Borenstein 2011, Wisskirchen 2017). A recent trend has been towards human–robot collaboration. For example, assistant robots can be employed in tasks such as carrying, handling, assembly, and measuring in manual environments. Even real time human–robot interactions are becoming feasible thanks to advancement in sensory technology (Kulić and Croft 2006, Van den Bergh et al. 2011). These developments greatly increase human workers' capacity to exploit their comparative advantage in perception, dexterity, and analytical decision-making (Hägele et al. 2001, 2002), but also the demand for complementary skills. Robotics has been associated with changes to organizational coordination to improve performance (Sergeeva et al. 2020), quality and value chain upgrading (De Backer et al. 2018), signalling an emergent General Purpose Technology (GPT) with radically new business models (Gambardella and McGahan 2010, Dixon et al. 2020) which require changes to firms' organizational structures from supply chain logistics (Tesoriero et al. 2009, 2010, Serpa and Krishnan 2018) all the way to flexible manufacturing solutions (Geismar 2015). Human and organizational capital are thus important intangible assets, yet existing studies have not paid sufficient attention to their complementarity to robotic technological capital. Although they have been shown to augment robot productivity along with other intangible capital such as R&D and branding (Gómez and Vargas 2012, Mutlu and Forlizzi 2008), the dynamic interaction with robotics is inadequately understood.

The productivity enhancement of intangible capital is widely documented (Corrado et al. 2012, Marrocu 2011, Roth and Thum 2013).[3] Becker (1962) pioneered the concept of human capital and that it accounted for a large proportion of cross-country economic disparity which differences in physical capital alone could not explain. Initially human capital emphasized formal schooling, but experiences, on-the-job training, and even tacit knowledge are increasingly viewed as vital components. Empirical studies demonstrate human capital to be an important driver of firm productivity (Black and Lynch 1996, Dearden et al. 2006, Kleis et al. 2012). The notion of organizational capital emerged later and encompasses various business practices, culture, processes,

[3] Corrado et al. (2012) empirically studied the role of intangible capital in the economy. They divided intangible capital into three broad categories. The first category is referred to as "computerized information," which consists largely of software and database systems. The second category is "innovative properties," which covers a diverse set of intangible capital encompassing R&D, design, financial innovation, mineral exploration, and artistic originals. The third is "economic competencies," which include branding and advertising, organizational capital, and training (human capital).

and structural relationships with internal and external stakeholders (Black and Lynch 2005, Brynjolfsson and Saunders 2010, Ennen and Richter 2010). According to Haskel and Westlake (2018), organizational capital is a key input for the creation of new business models. New business models are effective at maintaining competitive advantage and productivity as the uniqueness of an organization is difficult to replicate (Brea-Solís et al. 2015, Lieberman et al. 2017). Business models are difficult to replicate because they are complex systems consisting of many interdependent components such as the activities related to the customer value proposition, how value is created, the means of capturing value and the partners required in the value network (Velu 2017).

Studies have shown that organizational capital contributes to enhanced productivity at the firm level, albeit often requiring complementary technological inputs (Bertschek and Kaiser 2004 Crespi et al. 2007). At the macro level however, productivity growth has declined even as investments in both intangible and technological capital dramatically increased. A possible reason may be the lack of effective complementarity between technology-intangible capital investments. The lacklustre growth in productivity at the economy level might be because new technologies have yet to establish widespread complementarity with business and organizational processes on a scale which pervades the entire economy and across multiple industries to become GPTs (Brynjolfsson et al. 2018).

Studies on complementarity may be divided into two main classes[4] (Ennen and Richter 2010). The first group investigates complementary assets via the interaction approach (Aral and Weill 2007,

[4] See seminal work by Teece (1986), which was one of the first systematic discussions of complementary assets and its effect on profitability. There are typically three forms of complementarity – strict complementarity where two asset functions together exclusively; weak complementarity whereby one asset enhances the performance of the other but they not required to function together; and super-modular complementarity whereby two assets enhance each other’s performance with positive feedbacks.

Bonaccorsi and Thoma 2007), which focuses on the interplay between specific categories of assets. The second group seeks to understand complementarity from a systems-based approach (Bresnahan et al. 2002, Hitt and Brynjolfsson 1997, Powell and Dent-Micallef 1997). We refer to the former as *direct complementarity* and the latter as *indirect* or *systems-based complementarity*. Systems-based complementarity tend to report larger magnitudes, which suggests that major productivity gains arise from complex systems interactions. The differential performance of otherwise similar firms may be primarily due to their different resource combination and hence complementarity rather than differential access to resources (Adegbesan 2009).

The technological-intangible complementarity literature focuses on ICT (Brynjolfsson and Hitt 2002, Bocquet et al. 2007, Gómez and Vargas 2012, Stucki and Wochner 2019, Saldanha et al. 2020). Brynjolfsson and Hitt (2002) found that ICT contributed to more efficient and responsive organizational structures by reducing the cost of information sharing and coordination. The demand for complementary skilled labor also increased as a result. Milgrom and Roberts (1990, 1995) theoretically modelled the complementarity between technology and intangible capital, showing the conditions that favor firms' joint investment in technology, human-resource, marketing and organizational inputs which cover a wide range of activities from production to sales. Brynjolfsson and Milgrom (2013) provided a detailed analysis of complementarity in the organizational context. Firms often face a plethora of simultaneous set of decisions such as technology adoption and organizational changes that display complementarity. Hence, these sets of decisions should be regarded as a complex interlocking system, where only altering one component of the decision can have unintended negative consequences on the performance of the firm. In addition, conflicts between old and new system practices can arise, and this may often be induced by the introduction of new technologies. Without proper business process redesign, company performance may even be adversely affected by new technology (McAfee 2002). Brynjolfsson et al. (1997) investigated the transition from traditional to “modern manufacturing” in Johnson and Johnson. Due to the established organizational process being heavily geared towards reducing changeover times, new flexible production equipment remained employed for long, unchanging production runs – the opposite of what was intended. This was the result of decades of accumulated heuristics and implies that existing organizational capital is often a poor complement to new production technologies including robots. Instead, new organizational capital will need to fit with new technology and this was ultimately what Johnson and Johnson did by forming an entirely new team at a restarted new site, where fresh organizational approaches rooted in modern manufacturing techniques were introduced.

A limitation of existing studies is the tendency to assume two assets to either be complements or not, negating the development of this relationship. Pickering’s (1993, 1995) *Mangle of Practice* offers a conceptual understanding of how two assets become complements over time. Pickering argued that the final outcomes that emerge are the cumulation of continuous interactive processes between various material and non-material (human) agents. Material agents refer to the functioning of the natural order, while non-material agents refer to human-directed forces, with the crucial distinction being that the latter possess intentionality. Pickering’s theory begins with human agents such as a scientist/engineer attempting to solve a particular problem through manipulating the passive forces of nature as a means to that end. However, many issues could not have been foreseen at the time and the material agents would generate resistance. In response, the human agents would seek solutions to accommodate them. Further problems may yet arise in time or as a consequence of the accommodation, leading to subsequent solutions being sought. This iterative process is termed “tuning” – analogous to the tuning of radio frequencies to the “correct” station. In addition to material and human agents, Pickering identified disciplinary agency, which is concerned with the establishment of rules, relations, and cultures in human agents such that they become entrenched over time. This promotes continuity but also creates a degree of inertia on the actions and activities of the human agents. In this context, the Mangle of Practice is consistent with the "logic of opposition" whereby opposing forces promote or impede change when studying technology-organizational relationships (Robey and Boudreau 1999).

Several studies have applied the tuning concept to explain the interaction between material and human agents within the firm. Barrett et al. (2012) examined the interaction between three groups of workers (human agents) – pharmacists, technicians, and assistants – and the temporal dynamic materiality of an automated system (material agent), affecting the skills, discretion, status and visibility of the worker groups. Martini et al. (2013) explored the mangle process via the context of dynamic social media platform where the website (material agent) configured in response to the engagement of different users (human agent). Similarly, Venters et al. (2014) studied tuning in relation to a computer platform for a community of particle physics researchers. Venters et al. (2014) extended Pickering's argument to temporal balancing between three goals for the past, present, and future. Ormerod (2014) investigated mangling in the UK energy sector. While most firm-level interaction is *micro-mangle*, Ormerod (2014) sought to apply the principle of *macro-mangle* (Pickering 1995, pp. 232–4). Macro-mangling represents tuning at a systems-wide level, reflecting adjustments of the underlying environment, such as a change in business model or organizational structure. Therefore, Pickering's mangle is a helpful theoretical lens to better understand the dynamics of the evolution of complementarity between assets over time.

HYPOTHESIS DEVELOPMENT

We apply Pickering's mangle to the context of robot adoption. The development of complementary assets with robot adoption over time may be illustrated as tuning between robots and firm workers, which represent material and human agency, respectively. The tuning process is affected by intangible capital, notably human and organizational capital. This is because human and organizational capital affect two critical functions of human agents – intentionality and disciplinary agency – respectively. Intentionality and disciplinary agency play a key role in the accommodation or adaptive process of human agents to the resistance of material agents, and it is this adaptation that gives rise to complementarity. Human and organizational capital, however, display different characteristics to their respective influence on the accommodation and adaptive processes.

Robot and human capital complementarity

Robot–human capital interaction is a form of direct complementarity, since human capital involves changes to mainly one component of the firm – the workforce – by improving the quality of the labor force. Although human capital may affect other firm components, such as via knowledge spill-overs, this happens indirectly (Battu et al. 2003).[5] Therefore, its complementarity with robots is likely to be bi-directional.

Following the introduction of new robots, many routine tasks become automated. Some workers might experience greatly diminished roles, in extreme cases being reduced to switching robots on and off (Noble 1986). This results in a reduction in workers' discretion, which suppresses intentionality, which in turn limits the options for human agents to respond effectively. This also

[5] This is often the case for entire sectors, especially relating to technology, such as IT sectors. Tambe and Hitt (2014) found that IT firms benefit from one another's investment in labor as a result of labor mobility between firms in clusters, contributing between 20% and 30% improvement in productivity.

stifles workers' innovative and creative abilities, which are necessary for adapting to the changing role of employment (Cronshaw and Alfieri 2003, Molleman and Van den Beukel 2007).

The suppression of intentionality may be compounded by a lack of capability on the part of the human agent. For example, workers may lack technical skills such as programming, practical skills such as cooperating with robots to exploit the division of labor, or human-oriented tasks such as design and management. Firms may therefore choose to invest in human capital such as training. The accumulation of human capital, however, would not be instantaneous but require tremendous input of resources. Workers are unlikely to be given discretionary authority until they become fully equipped, further hindering the adjustment process and causing workforce resistance with management (Courpasson et al. 2012).

In the short term there are interrelated factors impeding robot adoption, which may be interpreted as resistance within Pickering's framework. First, there is management's inability to allow greater flexibility to workers to adapt to the new robotically automated environment, causing workers to lack discretion and/or capability to exercise their intentionality. Second, there is the disruption caused by diverting worker time towards new training. Therefore, in the short term the relationship between human capital and robots is likely to be dominated by resistance rather than accommodation. We therefore posit our first hypothesis, as follows:

> *Hypothesis 1: In the short term, investing in human capital reduces the productivity-enhancing effects of robots.*

In the long term, however, the investment in human capital will begin to yield payback. The human capital stock equips workers with the skills that, when combined with intentionality, produce effective accommodation to new robot installation. Such accommodation is achieved through two mechanisms. First, there is the tendency for technology, when combined with human capital, to increase information-sharing, thereby devolving the decision-making process (Brynjolfsson and Hitt 2002). This encourages the input of workers at all levels of the firm, increasing their ability to work independently as the hierarchy is reduced. Second, the workers themselves also become more capable. Human capital displays a form of "adaptive complementarity" whereby initial investment tends to empower learning and adjustment in order to be more accommodative of the new robotically automated environment (Appelbaum and Albin 1989, Teixeira and Fortuna 2010). Therefore, human capital, once formed, becomes an asset to the firm, which generates positive direct complementarity with robots. We posit our second hypothesis as follows:

> *Hypothesis 2: In the long term, investments in human capital increase the productivity-enhancing effects of robots.*

Robot and organizational capital complementarity

While human capital and robots display direct (bi-directional) complementarity, the complementarity of robots with organizational capital is systems-based and multi-directional. When new robots are installed, there is often a mismatch with the current organizational structure designed for a previous-generation technology, creating resistance, thereby limiting full efficiency. Sandberg et al. (2020) utilized complex adaptive systems (CAS) theory to explore the organizational shifts induced when platforms become automated and more digitalized. The increased dynamism and interconnectivity induced unexpected major architectural organizational change toward an ecosystem-oriented logic.

In the short term, as an accommodation response, the management of the firm implements new organizational practices, structures and business models in order to align more closely with the robot-centric production model. The changes would need to be affected on the components of the business model, including the content, structure and governance, in order to achieve better alignment with the new robotic investments. Such changes create a new disciplinary agency, with the establishment of new rules, relations, and cultures within the firm, which help with better alignment between the business model and the new robots. Therefore, investment in organizational capital empowers disciplinary agency and enables changes in the cognitive frame of the senior management, as well as the activity system of the business model. Hence new organizational capital and robots are complementary and we posit the third hypotheses:

Hypothesis 3: In the short term, investments in new organizational capital increase the productivity-enhancing effect of robots.

Disciplinary agency is invaluable in ensuring continuity yet by its very nature also instils organizational inertia in the long term. This hinders further organizational changes, even if they are necessary. The firm’s management could become locked into a cognitive mindset and might be unable to reframe. While an existing business model can be successful in commercializing the value of technology (Dmitriev et al. 2014, Gambardella and McGahan 2010), it can also create lock-in effects (Zott and Amit 2010). During times of emerging disruptive and discontinuing technology, such threats increase dramatically for incumbent firms (Rothaermel and Hill 2005, Tongur and Engwall 2014). This *cognitive challenge* means that the firm’s management is unable to reframe and adapt the business model accordingly (Velu 2017). Firms generally lack the ability to fundamentally reconfigure their functions architecturally due to internal resistance as what is best for the firm might not be optimal for any business unit (Velu and Stiles 2013). As a result, changes are typically piecemeal and strategically incoherent, the result of compromises whereby firms face the challenge of reconfiguration.

The organizational rigidity caused by disciplinary agency exacerbates both the cognitive and reconfiguration challenge in the long term. Hence, in contrast to human capital, organizational capital displays less "adaptive complementarity," as disciplinary agency builds inertia into the business model system, which causes certain elements of legacy organizational capital to be unresponsive to the requirements of new robots. Based on this observation, we posit our fourth hypothesis:

> *Hypothesis 4: In the long term, investments in organizational capital reduce the productivity-enhancing effects of robots.*

DATA AND METHODS

Data

We primarily utilize data from three sources – the International Federation of Robotics (IFR), Intaninvest (Corrado et al. 2016), and the European Union Capital Labour Energy and Materials (EUKLEMS) database. The first source supplies us with data on the deployment of robotics across various countries and industries; the second on expenditure in various forms of intangible capital; and the third provides other data necessary for the control variables, such as investment in physical capital.

Error! Reference source not found. shows the temporal changes in the average values of key variables of our study. Average productivity in robot–using industries have increased only slightly, despite steadily rising levels of robot intensity for all countries, the five largest economies, and manufacturing, which highlights the "productivity paradox." Likewise, the stock of human and organizational capital has risen substantially.

Insert Figure 1 about here

The IFR records the number of industrial robots deployed in each country, industry, and year. In order for a machine to be counted as a robot by the IFR, it must satisfy the International Organization for Standardization's (ISO) definition ISO 8373 of being "an automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which may be either fixed in place or mobile for use in industrial automation applications." The EUKLEMS database standardizes across EU member states (as well as the US) regarding key economic metrics such as output, employment, and capital formation. It also covers input data such as wages and material costs. Both the IFR and EUKLEMS summarize data down to two-digit Standard Industrial Classification (SIC) codes and also cover similar time spans starting from the late 1990s.

Similarly, Intaninvest harmonizes investments in intangible assets in the EU (plus US and Japan), broken down by sector and years. However, because of the data aggregation involved, Intaninvest reports data at one-digit SIC. Investments in intangible capital are broken down into three main categories consisting of "software and database," "innovative properties," and "economic competencies," of which the latter two may be sub-divided further. We are primarily interested in the "economic competencies" category, which consists of "branding," "organizational capital," and "training", and specifically the final two. The time period covered by Intaninvest runs from 1995 to 2015 which is similar to IFR and EUKLEMS. We employ a panel data structure, with the cross-sectional variable being specific country–industry pairs. We compile annual data for the period 1995–2015 in 18 European Union (EU) countries. Our sectoral breakdown is based on five major industrial sectors (one-digit SIC) in order to use the Intaninvest data.

Insert Table 1 about here

Table 1 lists all the countries and sectors included, which covers all the countries in the Intaninvest database. The EU-only analysis has the advantage of comparing countries that have relatively similar institutions and economic development, and which are increasingly integrated into a common economic zone. Unless otherwise stated, all variables are expressed as per labor unit (i.e. divided by employment size), and all monetary values are based on the 2010 price index, which is the base year specified in both the Intaninvest and EUKLEMS databases. The monetary values are also all based on Euros, which was introduced in 2002 across the Eurozone countries. Intaninvest and EUKLEMS have both reported and standardized pre-2002 values into Euro equivalents. Five countries in our dataset do not use the Euro – Czech Republic, Denmark, Hungary, Sweden and the United Kingdom. For these countries we converted the national currencies to Euro based on the 2010 exchange rate, the same as the base year. Table 2 provides a summary of the data that we use and the descriptive statistics. Table 3 displays the correlation matrix of the variables.

Insert Table 2 about here

Insert Table 3 about here

Dependent and independent variables. For our dependent variable we use the Gross Value Added (GVA) obtained from the EUKLEMS database, which provides detailed sectoral values at national level for EU countries. When GVA is divided by the employment we obtain GVA per worker, which is a standard measure of productivity. The main independent variable of robot stock is obtained from the IFR database. The IFR records shipment of industrial robots down to a two-digit SIC code.[6] In addition, the IFR produces values for the implied stock of industrial robots. The values were derived by assuming an effective life of 12 years. This measure of stock is problematic for two reasons. First, the life of many industrial robots is often much longer than 12 years, especially for newer generations of robots (though this does not account for the possibility of obsolescence as a result of, say, technological change). Second, the progressive deterioration of the robot is not accounted for during its lifespan. Instead we construct our own measures of robot stock based on the perpetual inventory method from the shipment data:

$$R_t = G_t^R + (1 - \delta_R) R_{t-1} \qquad (1)$$

R_t and G_t^R refer to the stock of robots and shipment of robots at time t, respectively. δ_R is the constant rate of robot depreciation. We assume that δ_R is 10% as the default but also experiment values in the range of 5–15% as part of a sensitivity analysis, following the procedure of Graetz and Michael (2018). We find that the different depreciation rates assumed do not significantly affect our results.

The other main independent variables of interest are the two forms of intangible capital – human capital and organizational capital, obtainable from the Intaninvest database. Human capital is proxied by expenditure in training at the firm level. As such this reflects training specific to the firms or the human capital workers received in work and not that already embodied by them, such

[6] As a result of this level of detail, for confidentiality purposes the IFR does not report the shipment values for any country–industry pairs consisting of four firms or fewer. Therefore, several country–industry values are discontinued temporally when the sector was small. For example, in a given year the shipment of robots to a particular country sector is omitted as a result of there being too few firms, but in the following year a value is reported when the country sector exceeds four firms. This would result in a spurious stepped "jump" in total robot shipment. In order to correct for this, we assume that the industry share of robot shipment in a country remains constant over time. Based on this share, we infer the missing year values of country–industry pairs from the years that they were reported, referencing the national aggregate shipment. This is also the approach adopted by Graetz and Michael (2018).

as general education and schooling (although this may affect the effectiveness of training). Organizational capital is available in Intaninvest as firm level (own-account, non-purchased) spending on organizational and business process re-engineering (Haskel and Westlake 2018). This would capture organizational restructuring which is associated with business model innovation, such as adding a new business unit to sell a new product line, or enhancing the existing business model such as servitization whereby manufacturers are increasingly providing new services for their products. For a description of the data in the Intaninvest database, please refer to Table 2. The Intaninvest reports only gross capital formation. We convert this into stock values for intangible capital using the perpetual inventory method similar to Equation (1).

$$I_t = G_t^I + (1 + \delta_I)I_{t-1} + I_0 \qquad (2)$$

I_t and G_t^I refer to the stock of intangible capital (human or organizational) and its gross formation at time t, respectively. δ_I is the constant rate of depreciation. Using the specifications set out in Carrado et al. (2012) and the manual in Intaninvest, we set the depreciation rate at 0.4 for both human capital (training) and organizational capital. I_0 denotes the initial stock of intangibles. We obtain the I_0 value by assuming the average ratio of fixed capital to human/organizational capital formation over the study period, inferring I_0 using the stock of physical capital (from EUKLEMS) in the initial year (1995).[7]

Control variables. For the control variables, we include software and the database from Intaninvest. The conversion to stock value also follows the perpetual inventory method assuming a depreciation rate of 0.315, which is the rate applied by EUKLEMS. This variable is included as

[7] This is likely to be an overestimate of I_0 since investment in intangible capital on a major scale began much later than investment in physical capital. Nonetheless, the regression results are insensitive to values of I_0, even when we assume I_0 to be zero, an underestimate.

a control given the critical role that ICT plays in productivity. Most studies investigating the productivity effects of robots have included some measures of ICT (Acemoglu and Restrepo 2018, Graetz and Michael 2018). In addition, we include the value of the remaining intangible capital by subtracting training, organizational capital and software/database from the total value of intangible capital, as reported in Intaninvest. We include two other control variables from the EUKLEMS database. First, there is the stock of fixed or physical (tangible) capital, which is an important factor as specified in input–output relationships and production function theory. It remains the main source of capital in an economy or firm in terms of value, consisting of buildings, plants, equipment, and machinery. Second, we include the wage bill, which captures the renumeration to labor, another factor of production. These two control variables therefore jointly account for the determinants of fixed capital and labor and are also included in previous studies (Graetz and Michael 2018, Acemoglu and Restrepo 2020).

Econometric model

In order to test the hypotheses developed in Section 3, we construct an econometric model to formalize the relationship between our dependent, independent, and control variables. We specify the following econometric model in an attempt to reflect the short versus long-term complementary relationships between robots with human and organizational capital.

$$\ln(y_{it}) = \alpha_0 + \alpha_i + \beta_r \ln(r_{it}) + \beta_{hs}\Delta \ln(h_{it}) + \beta_{hl} \ln(h_{it}) + \beta_{os}\Delta \ln(o_{it}) + \beta_{ol} \ln(o_{it}) + \beta_{rhs}\Delta \ln(r_{it}) \ln(h_{it}) + \beta_{rhl} \ln(r_{it}) \ln(h_{it}) + \beta_{ros}\Delta \ln(r_{it}) \ln(o_{it}) + \beta_{rol} \ln(r_{it}) \ln(h_{it}) + \beta_x x_{it} + \varepsilon_{it} \tag{3}$$

In the above equation all variables are expressed as per worker unit. y_{it} is the dependent variable denoting output per worker; r_{it} robot per worker; h_{it} human capital per worker; o_{it} organizational capital per worker; and x_{it} a matrix of control variables per worker. The terms α_0, α_i and ε_{it} refer to the time-invariant intercept, individual-specific heterogeneity, and the error term, respectively. The subscripts i and t denote, respectively, the country–industry pair and time (year), while the coefficients are expressed as the β values with various subscripts. The notation Δ represents first-difference or change.

Previous studies have demonstrated the positivity of β_r, yet to the best of our knowledge no study has examined the moderating effects of human and organizational capital on robot productivity, as represented by β_{rhs} and β_{ros} in the short term and β_{rhl} and β_{rol} in the long term. This is because the first-difference terms reflect an incremental change and the instantaneous effect of the interactions on productivity. As a flow variable, the change in the interactions captures the investment, expenditure, or capital formation in the intangibles but also includes depreciation and can therefore be regarded as the net change in effective stock.[8] The stock variable on the other hand reflects the cumulative activities over multiple periods and hence can be interpreted as reflecting long-run relationship.

With *Hypotheses 1* to *4*, we expect the interactive coefficients to be of the following signs, respectively: $\beta_{rhs} < 0$, $\beta_{rhl} > 0$, $\beta_{ros} > 0$, $\beta_{rol} < 0$.

We employ a fixed-effects panel data model to estimate the coefficients. The greatest advantage of this model compared to the random-effects model is the functional transformation, which eliminates α_i, the time-invariant heterogeneity. Otherwise, we will be forced to assume that $cov(\alpha_i, \varepsilon_{it}) = 0 \ \forall \ t$, an often unrealistic assumption.

[8] Instead of $\beta_{rhs} \ln(r_{it}) \, \Delta \ln(h_{it})$ and $\beta_{ros} \ln(r_{it}) \, \Delta \ln(o_{it})$, which is an alternative specification, we adopt the functional forms, as shown in Equation (3) above. This is because we wish to see the effect of new intangibles combined with new robotic equipment rather than with the old stock.

Addressing potential endogeneity on the productivity effect of robots

As Graetz and Michael (2018) and other studies have identified, the relationship between robots and productivity may be subject to endogeneity bias. Endogeneity may occur for three reasons: first, via reverse causality, where most productive firms choose to pursue robotic automation and other technological upgrades in the first place, also known as the self-selection bias; second, the relationship between robots and productivity may be determined simultaneously; and, third, robot adoption may be correlated with some omitted variables, which are the real drivers of productivity.

In an attempt to limit the potential bias in our coefficient estimates due to endogeneity, we employ an Instrumental Variable (IV) in a Two-Staged-Least-Squares (2SLS) panel fixed-effects model. We construct a metric of the percentage of the workforce that are potentially replaceable with robots. We do this by first matching the IFR robot "Application" list with occupations in the International Standard Classification of Occupations (ISCO) list at the three-digit level, which is a relatively detailed breakdown of occupations and roles. Any ISCO three-digit occupation that is matched is potentially replaceable by robots since they involve roles that are currently undertaken by robot applications, as listed in the IFR. Next, we aggregate the total amount of employment in the matched ISCO by one-digit SIC codes, which corresponds to our data in Intaninvest, for each country–industry–year, using the occupation–industry cross-tabulation employment figures provided by Eurostat through the Labour Force Survey. Finally, the total employment obtained in this way is divided by total employment to obtain an estimate for the percentage of the workforce potentially replaceable by robots. Note that this should define a lower limit given that the match is with current robots without accounting for technological improvements, which may substantially enlarge the list of tasks/applications performed by robots in the near future.

Accounting for firm level interaction effects

Our hypotheses and the associated mechanisms are all described at the firm level, hence it would have been ideal to conduct the empirical analysis using firm level data. Whilst our data were collected at the firm level they are reported at the aggregate industry-country level. This may hinder direct observation of firm level behaviors. We attempt to mitigate this problem by accounting for two dynamic interactions at the firm level which may have industry level consequences. First there is likely to be inter-firm displacement. Firms which invest in robot and complementary intangibles may indeed substantially raise its productivity (and employment) but at the expense of competitors which do not invest. The net result at the industry level is either negligible or even negative (Acemoglu et al. 2020). Second, there may be positive spill-overs between firms due to competition where investments in robot and intangibles by one firm induces others to invest as well and hence raise the overall productivity relative to other industries. The degree to which firms interact in these two ways are likely to be influenced by a) structural shifts in an industry and b) firm concentration, as both of these factors provide an indication of the competitive dynamics between firms. We specify two IVs to measure a) and b) for which there are accessible data at the industrial level. These competitive dynamics are likely to impact firm responses in a systematic way at the industrial level which in turn affects both the displacement and positive spill-overs. The human and organizational capital are now treated as endogenous as our chosen IVs are likely to affect the investment decisions by altering their level of complementarity and rates of return (see Brynjolfsson and Milgrom 2013, pp. 45). Robot adoption is also treated as endogenous as the IVs may also influence technological decisions.

For the first IV to measure structural shifts in an industry, we construct an index which captures firms' business model changes. A recent paper by Wannakrairoj and Velu (2021) used the absolute change in turnover to asset ratio (also known as the Asset to Turnover ATO ratio) to proxy for business model innovation by firms. A firm's ATO ratio is likely to remain largely stable unless it undergoes significant changes. The ATO ratio may change significantly if a firm decides to radically alter its underlying business model. For example, a traditional bricks and mortar bookseller is likely to hold very large stocks of inventory in books and other assets which it owns. Consequently, it has a relatively low ATO ratio. On the other hand, an online book retailer with significant third-party suppliers will own a far smaller proportion of the inventory in central warehouses and perhaps use more robotics technology to help fulfil orders compared to a traditional bricks and mortar bookseller. Its business model may be similar to that of an online platform which generates revenue by charging commission from transactions. As a result, it has a higher ATO ratio compared to a traditional book retailer. Should a traditional bookseller decide to transform into an online seller or at least add e-commerce to its business model, then its ATO ratio may move in that direction. The reverse situation is also possible whereby an online book retailer invests in brick and mortar units to increase its physical presence.

In order to approximate the absolute change in ATO ratio as measured in Wannakrairoj and Velu (2021), we gather data on the absolute change gross output (fixed) capital stock ratio at the industry level. Gross output and capital stock may be interpreted as the industry equivalent of turnover and asset, respectively. Firm level idiosyncrasies are unlikely to significantly affect the gross output to capital stock ratio, which will only change in response to major industrywide shifts in trends, such as e-commerce becoming more mainstream and adopted by most firms. The absolute change in gross output to capital stock ratio therefore signals structural shifts that should induce most firms to alter their business models in a similar way in response to robot adoption. Dixon et al. (2020) for example found that robot usage led to the decentralization of decision making for day-to-day activities but centralization for strategic decisions. This suggests that firms have put in new flexible managerial systems to allow for the two processes simultaneously, hence the demand for organizational capital may increase. Furthermore, Dixon et al. (2020) reported a reduction in managerial relative to non-managerial staff and that robot is positively associated with training in professional and computer hardware training but not with managerial and office type training. This suggests higher demand for new training and human capital due to robots. The absolute change in gross output to capital stock ratio therefore is likely to affect human and organizational capital.

For the second IV to measure firm concentration, we construct two Herfindahl-Hirschman (HH) indices to reflect the degree of firm concentration at the country and industry level in order to capture the competitive dynamics. These are expressed by Equations (4) and (5) below, respectively:

$$HH_{it} = \sum_{c=1}^{18} s_{ict}^2 \tag{4}$$

$$HH_{it} = \sum_{i=1}^{5} s_{cit}^2 \tag{5}$$

Where $c = 1,2, \dots 18$ denotes the countries in our dataset; $i = 1,2, \dots 5$, the industries; s_{ict} denotes the share of firms of country c in industry i, at year t; whereas s_{cit} denotes the share of firms of industry i in country c, at year t. HH indices are frequently used to compute the degree of value concentration, with a range between 0 and 1, where 0 indicates perfect dispersion while 1 shows perfect concentration.

This set of HH indices detect the extent to which firms in a given country/industry are clustering at these levels. High levels of firm concentration may exist in a few countries for a given industry, for example Germany is very dominant in manufacturing, while a particular country may have firms concentrated in a small number of industries. The former implies geographical clustering of firms in an industry while the later indicates industrial specialization at the country level. These are likely to affect incentives to invest in intangible capital. For example, higher geographical firm clustering may mean greater competition which encourages rapid investments in technology (robots) and organizational capital to generate competitive advantages via their unique complementarity. It may on the other hand disincentivize firm specific training if there are significant positive externalities due to for example high risk of employee turnover to competitor firms. The degree of competition at the industry/country level is therefore likely to also impact human and organizational capital.

RESULTS

The results in Table 4 show that robot per worker is positively associated with productivity, in accordance with previous studies. The elasticity coefficients β_r range from 0.204 to 1.076, comparable to that reported by Graetz and Michael (2018). This reinforces previous findings that robots contribute positively to productivity.

Insert Table 4 about here

The results in Table 4 are also in line with our hypotheses. We show the baseline non-interactive regression in Model 1, a reference to compare the other models. Models 2-5 show the interactive terms between robot and intangible capital which are central to our hypotheses. The interaction between robot and human capital in the short term is negatively and significantly associated with productivity, in accordance with *Hypothesis 1* ($\beta_{rhs} < 0$). This is seen in the seventh row of Model 2 where our result displays a negative coefficient ($\beta_{rhs} = -0.334$), significant at the 1% level. In the long term the results show positive and significant robot–human capital interaction in row eight

($\beta_{rhl} = 0.0284$). This supports the predictions of *Hypothesis 2* ($\beta_{rhl} > 0$). The interaction of organizational capital with robots is positive and significant with respect to productivity in the short term, as seen by the positive coefficients in row nine ($\beta_{ros} = 0.392$), in line with *Hypothesis 3* ($\beta_{ros} > 0$). Lastly, in the long term, organizational capital and robot interaction is negatively associated with productivity, as seen in row ten ($\beta_{rol} = -0.0527$), in line with *Hypothesis 4* ($\beta_{rol} < 0$). An important point to note is that the positive short-term complementarity between robot and organizational capital is considerably larger than the long-term complementarity between robot and human capital (0.392 vs 0.0284). The main control variables are also generally of the expected sign. Software and database, other intangible capital, fixed capital, and wages are all positively associated with productivity.

In Model 3 we show our results when applying a 2SLS model, accounting for possible endogeneity between robot density and productivity. When robot per worker is instrumentalized with the proportion of jobs in a country-industry year which are automatable, the robot coefficient remains positive and significant. In fact, the magnitude is substantially enlarged from 0.237 to 1.076. Our hypotheses still hold as this model produces coefficients in the expected direction which are statistically significant with $\beta_{rhs} = -0.286$, $\beta_{rhl} = 0.0342$, $\beta_{ros} = 0.313$ and $\beta_{ros} = -0.406$ for hypotheses 1 to 4, respectively. The coefficients are comparable to Model 2 with the exception of the fourth hypothesis where the negative interaction between robot and organizational capital on productivity is substantially larger (-0.0572 vs -0.406).

In Model 4 the result shows a structural equation model where not only the robot but also the endogenous variables of human and organizational capital are treated as endogenous, which we attempt to exogenize using IVs to reflect the dynamics of firm interactions which may affect aggregate productivity. In this way we hope to overcome at least partially the limitation of using aggregate data to test for theoretical constructs at the micro firm level. We also set robot density as endogenous, just like in Model 3. This is because it is very conceivable that structural and organizational changes induced by new business models for example may affect decisions to adopt new technologies, such as robotics. The results of Model 4 show that the coefficient for robot density remains very similar to the 2SLS model at 1.031 but much larger than Model 2. The four hypotheses also remain supported by the result, with coefficients of $\beta_{rhs} = -0.797$, $\beta_{rhl} = 0.0686$, $\beta_{ros} = 0.744$ and $\beta_{ros} = -0.408$ all of which are significant to at least the 5% level. Compared to the previous Model 3, the absolute magnitudes of the coefficients are even larger often by a factor of 2-3. Model 5 is identical to Model 4 with the exception that robot density is treated as exogenous like in Model 2. Once again the coefficients of interest all conform to our hypotheses in terms of their signs and significant to at least the 5% level (the coefficients are $\beta_{rhs} = -1.155$, $\beta_{rhl} = 0.0847$, $\beta_{ros} = 1.060$ and $\beta_{ros} = -0.135$, respectively).

DISCUSSION

Our analysis finds that robot per worker is associated with higher productivity at the country–industry level in 18 EU countries between 1995 and 2015, in accordance with previous studies. In addition, the results support our hypotheses with regards to the different moderating roles of human and organizational capital in improving productivity from robots, for both the short and the long term. Robot–human capital interaction reduces robots' productivity enhancement effect in the short term but increases it in the long term. The reverse relationship holds for robot–organizational capital interaction. The different dynamics shown by human and organizational capital are attributable to their different nature. We hypothesised that human capital functions as a direct complement, while organizational capital develops systems-based complementarity. These observations hold even when we apply a structural equation model to account for possible interactions between firms. This is important since our data though originally collected from firm level accounts are reported as industry aggregates.

Our findings reveal the influence of intangible capital in unlocking the full productivity potential of robots. Human capital acts as a catalyst to accelerate the “tuning” process and enables human agents to adjust to major technological installations such as robots by facilitating intentionality and capability. Organizational capital, on the other hand, creates new systems of organizational structures and business models to facilitate the new technology. However, in the long-term disciplinary agency is responsible for developing organizational inertia. This restricts further organizational changes to subsequent rounds of technological adoptions, making legacy organizational capital incompatible with the installation of new robots, similar to the Johnson and Johnson flexible manufacturing example Brynjolfsson et al. (1997) referred to. In other words, organizational capital compared to human capital is less able by itself to “tune” to the new technology and explicit managerial intervention may be necessary.

Implications for theory

Our study has important implications for future work relating to the adoption of robots and other technologies. First, the productivity enhancement effect of robots and other technology should not be considered in isolation. The complementarity with intangible capital is critical for reaping the full productivity potential. Second, attention should be paid to the type of complementarity that is likely to be formed, whether direct or systems–based. The former may be exemplified by robot–human capital, and the latter by robot–organizational capital interactions. The distinction in complementarity types is applicable to the study of other intangible capital, such as branding and R&D, depending on the relevant technological context, as well complementarity between various forms of intangible capital.

Third, there is a need to understand the dynamics of how complementary relationships are formed, and not simply whether two assets are complements. This is particularly important, as studies have shown how social–technical systems should be understood from the perspective of complementarity (Teece 1986, 2014). Pickering's theory provides a useful framework to assist in such an understanding. Initially, for various reasons, two assets may not be complementary, or worse, function as negative complements, due to the resistance of material and/or human agents. Over time however, positive complementary relationships can be established that facilitate the accommodation process. The reverse situation is also possible, whereby initially complementary assets become incongruent over time as previous synergy fades. The first situation is illustrated in this study by the relationship between robot and human capital, and the latter by the relationship between robot and organizational capital.

Fourth, legacy organizational capital may embody rigidity which limits business model innovation, and which could be explicated through Pickering's concept of disciplinary agency. In particular, the mechanisms through which the disciplinary agency changes in other scientific domains could contribute to a more nuanced understanding of cognitive and implementation challenges in the context of business model innovation following the adoption of digital technologies.

Finally, the development of complementary relationships, or lack thereof, may partially explain the productivity paradox for robot-using sectors. Perhaps the right kinds of skills among the workforce have not yet reached its full technological maturity, restricting human-robot complementarity. More crucially perhaps, past organizational capital prevents the acceptance of new business models tailored to the requirements of more recent robotics technology. The much larger short-run robot-organizational capital versus long-run robot-human capital coefficients suggest that complementarity which takes place at the level of entire organizations has the largest productivity improvement potential, consistent with the findings of Ennen and Richter (2010). We may not witness substantial productivity gains from robots and other technology until and unless there is widespread complementary business model innovation.

Implications for practice

Our study sheds light on the need to incorporate intangible capital, particularly human and organizational capital, when firms adopt new robots and other technology. The interaction process however may create productivity enhancements or hindrance depending on the stage of the complementarity formation. Firms should treat complementarity as a cycle instead of a static process. For robot-human capital complementarity, the initial phase of the cycle may involve mostly hindrance before an enhancement, while the opposite is the case for robot-organizational capital. With regards to human capital, the greatest challenge for management is perhaps how much discretion to give to workers to exploit the newly acquired human capital while avoiding the risks associated with an entirely new robotic work environment. However, in order to reap the benefits of human capital investments, managers need to realize the advantages of allowing some level of delegated responsibility to workers in order to adjust to a set of new work practices to accommodate the robotic environment whilst maintaining control of the coherence of the processes. In addition, firms might find it challenging to develop consistent investment criteria for organizational capital. This is riskier, since, as an indirect and systems-based complement, it concerns multiple elements and the adjustment of complex relationships. Managers need to develop a more integrated coherence scorecard measure to assess system level complementarity of organizational capital investments (Velu 2020).

Complementarity may be subjected to similar laws of depreciation and require periodic investments to maintain and enhance its effectiveness. If such is the case, complementarity should not be taken for granted and firms need to actively maintain existing complementarity and/or invest in new complementary relationships, perhaps even managing a portfolio of complementary relationships. Where possible, firms should consider applying conventional investment and cost-benefit criteria to assess their degree of complementarity of assets. However, even conceptual identification of specific complementarities in firms can be challenging, let alone their objective quantification. Nonetheless, managers should endeavor to move in this direction, beginning to develop appropriate methodologies to assess complementarity of intangible and tangible assets in firms. Management should increasingly regard complementarity as an asset in and of itself.

CONCLUSION

In this study we have examined whether robots contribute to productivity, and whether this relationship is moderated by intangible capital – human and organizational capital. We find that robots contribute significantly to productivity, in accordance with previous studies. We also find that in the short-term human capital has a negative effect on the productivity enhancement of robots but a positive effect in the long term. The moderating effect of organizational capital is the precise opposite: a positive effect in the short term but a negative effect in the long term.

Our study makes three main contributions. First, we contribute to a nuanced understanding of the relationship between intangible capital and the effect of robots on productivity in the short and long term. Second, we contribute to the complementarity literature by showing the dynamics of how assets become complements, or not, over time, depending on the type of complementarity. Third, we contribute to the business model literature by showing how organizational capital investments influence productivity following the adoption of new robotic technologies. In doing so, we provide a nuanced explanation of the recent productivity paradox.

The study begins to probe certain questions regarding the complex issue of robot adoption, its interaction with intangible capital, and the business model implications. With the growing realization of intangible assets, perhaps higher-resolution firm-level data will become available in the future to explore such a relationship in more detail. Robots present an immense opportunity to transform production, and as they continue to permeate all corners of the economy we may finally begin to witness rapid productivity improvements. This, however, is unlikely to happen without the complementarity of intangible assets, most notably of human and organizational capital.

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Table 1. List of countries and industrial sectors included in the data

List of countries included	Austria; Belgium; Czech Republic; Denmark; Finland; France; Germany; Greece; Hungary; Ireland; Italy; the Netherlands; Portugal; Slovakia; Slovenia; Spain; Sweden; the UK
List of industrial sectors included	“Agriculture, forestry and fishing”; “Mining and quarrying”; “Manufacturing”; “Electricity, gas and water supply”; “Construction”

Table 2. List of data variables, summary, and descriptive statistics at the country-industry level, 1995-2015

No.	Variable	Description	Variable type	Unit	Mean	S.D.	Min	Max	Source
1	Productivity	Gross value added (GVA) per worker	Dependent	Euros (2010)	121,355	279,573	4,760	3,391,239	Intaninvest
2	Robot per worker	Robot stock via perpetual inventory method, 10% depreciation, per worker	Independent; endogenous	Number of robots	1204.783	2712.931	0	18191.74	IFR
3	Human capital per worker	Stock of human capital (proxied by training) via perpetual inventory method, 4% depreciation, per worker	Independent	Euros (2010)	9,582	39,412	0	685,329	Intaninvest
4	Organizational capital per worker	Stock of organizational capital via perpetual inventory method, 4% depreciation, per worker	Independent	Euros (2010)	22,381	169,491	20	4,320,429	Intaninvest
5	Software and database per worker	Stock of software and database capital per worker via perpetual inventory method, 3.15% depreciation, per worker	Control	Euros (2010)	2,859	4,854	0	66,991	Intaninvest
6	Other intangibles per worker	Stock of remaining intangible capital, deducting human, organizational and software capital, per worker. Perpetual inventory method at 3% depreciation	Control	Euros (2010)	24,960	45,427	5	406,429	Intaninvest
7	Fixed capital	Stock of fixed capital per worker, obtained from gross fixed capital formation (GFCF)	Control	Euros (2010)	2,434,541	7,935,738	0	76,026,110	EUKLEMS
8	Wage rate	Wage or labor compensation per worker	Control	Euros (2010)	27,369	20,360	708	123,400	EUKLEMS
9	Employment	Number of persons engaged	For calculation (not in regression)	Number of persons	570,271	1,084,520	2,000	8,040,000	EUKLEMS
10	Potentially replaceable employment	Proportion of workers potentially replaceable by robots by matching IFR robot applications with ISCO occupation list aggregated to the country-industry level	Instrumental variable (for calculating 2SLS)	Percent	14.39%	13.72%	0	67.69%	Eurostat occupation-sector tabulation
11	Absolute change in output to capital ratio	The absolute change in the gross output to (fixed) capital stock ratio	Instrumental variable (between firm interaction)	Absolute change	0.813	5.690	0.00000343	80.790	EUKLEMS (author constructed)
12	HH index of country firm concentration	Herfindahl-Hirschman index of concentration of firms across industry at the country level	Instrumental variable (between firm interaction)	0-1	0.500	0.172	0.337	0.960	EUKLEMS (author constructed)
13	HH index of industry firm concentration	Herfindahl-Hirschman index of concentration of firms across country at the industry level	Instrumental variable (between firm interaction)	0-1	0.128	0.0385	0.0908	0.492	EUKLEMS (author constructed)

Table 3. Correlation matrix of all variables

No.	1	2	3	4	5	6	7	8	9	10	11	12	13
1	1												
2	0.2522	1											
3	0.0929	-0.0232	1										
4	0.0056	-0.039	0.2588	1									
5	0.3428	0.1296	0.0697	0.0306	1								
6	0.7682	0.3053	0.059	0.0223	0.3799	1							
7	0.1447	0.0159	0.7343	0.2641	0.0211	0.0772	1						
8	0.5449	0.3189	-0.0505	-0.0704	0.5493	0.5944	-0.0366	1					
9	-0.1225	0.4969	-0.0712	-0.046	-0.0533	-0.0636	-0.1175	-0.0129	1				
10	-0.1904	0.279	-0.026	-0.0364	-0.1039	-0.0945	-0.1179	-0.0551	0.2901	1			
11	-0.0238	-0.0582	-0.0328	-0.0192	-0.0664	-0.0694	-0.0422	-0.1204	-0.0383	0.0678	1		
12	-0.1674	-0.2034	0.1702	0.2048	-0.2316	-0.166	0.1721	-0.311	-0.1743	0.0419	0.214	1	
13	-0.1688	-0.1797	0.0317	0.1069	-0.049	-0.2452	-0.0666	-0.3759	0.1117	-0.1423	0.1038	0.174	1

Table 4. Elasticity relationship of productivity with the independent, interaction, and control variables

Dependent variable: GVA per worker	Model 1	Model 2	Model 3	Model 4	Model 5
Robot (β_r)	0.204***	0.237***	1.076***	1.031***	0.333***
	(0.0174)	(0.0283)	(0.131)	(0.213)	(0.0978)
Human capital 1st diff (β_{hs})	-0.128**	-0.0457	-0.0493	2.288	3.823**
	(0.0536)	(0.0543)	(0.0669)	(1.597)	(1.824)
Human capital (β_{hl})	0.124***	0.120***	0.198***	-2.093	-3.079**
	(0.0106)	(0.0129)	(0.0198)	(1.289)	(1.416)
Organizational capital 1st diff (β_{os})	0.241***	0.0896	-0.146*	0.360***	0.409**
	(0.0538)	(0.0552)	(0.0767)	(0.134)	(0.171)
Organizational capital (β_{ol})	-0.0285***	-0.0361***	-0.0111	-0.213	-0.361**
	(0.00901)	(0.00916)	(0.0119)	(0.139)	(0.147)
Robot x human capital 1st diff (β_{rhs})		-0.334***	-0.286***	-0.797**	-1.155***
	-	(0.0420)	(0.0523)	(0.351)	(0.380)
Robot x human capital (β_{rhl})		0.0284***	0.0342***	0.0686**	0.0847**
	-	(0.00961)	(0.0119)	(0.0296)	(0.0341)
Robot x organizational capital 1st diff		0.392***	0.313***	0.744**	1.060***
(β_{ros})	-	(0.0448)	(0.0565)	(0.315)	(0.321)
Robot x organizational capital (β_{rol})		-0.0527***	-0.406***	-0.408***	-0.135**
	-	(0.0171)	(0.0572)	(0.0842)	(0.0554)
Software and database (β)	0.0659***	0.0715***	0.0772***	0.0471	0.0335
	(0.0189)	(0.0186)	(0.0229)	(0.0341)	(0.0427)
Other intangible capital (β)	0.0473***	0.0396**	-0.0627**	0.0134	0.152
	(0.0168)	(0.0166)	(0.0256)	(0.0798)	(0.0959)
Fixed capital (β)	0.0407***	0.0361***	0.0323***	0.0276**	0.0219
	(0.00481)	(0.00474)	(0.00587)	(0.0139)	(0.0165)
Wage (β)	0.216***	0.260***	0.192***	0.334**	0.447**
	(0.0261)	(0.0263)	(0.0340)	(0.169)	(0.183)
Intercept	2.920***	2.831***	3.056***	2.587***	2.203***
	(0.0662)	(0.0660)	(0.0882)	(0.381)	(0.372)
N:			1800		
R^2:	0.669	0.677	0.313	0.215	0.286

*, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively

Figure 1. Changes in values of key variables for robot-using countries and sectors 1995-2015