Productive Robots and Industrial Employment: The role of national innovation systems

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this version, 12 August 2020

Abstract

We examine robot-labour substitutions in manufacturing and some other sectors in industrial countries. We show that the degree of substitution depends on demand and production elasticities. In multi-country empirical work its sign and magnitude crucially depends on a country's innovation environment. Making use of World Economic Forum data we estimate that countries with poor innovation capabilities substitute robots for workers but countries with richer innovation capabilities complement them. In non-manufacturing and transport equipment robots and workers are stronger substitutes than in other manufacturing. Our results can be rationalized by appeal to both firm objectives and international trade.

Keywords. robots-employment substitution, innovation enviromnent, company objectives, industrial allocations

JEL classifications. J23, L6, L21, O33, O52

*We thank Guy Michaels and Soo Hee Lee for commnets and the European Research Council for financial support through its Advanced Grant *Employment in Europe,* based at the University of Cyprus, 2013-2019 (FP7/2007-2013)/ ERC grant agreement n° 323940 ERC AdG 2012, Acronym: EUROEMP).

Extended abstract

The price of self-controlled industrial robots has fallen substantially in recent years, inducing a large increase in their use. This led many authors to investigate their impact on employment, with fears that robots are taking jobs away from workers. At first sight these fears appear justified. The vast majority of robot use is in manufacturing and manufacturing employment has been steadily falling for many years. In this paper we investigate this question with data from fourteen counties, thirteen from Europe and the United States. We focus mainly on manufacturing, although we also study three non-manufacturing sectors, agriculture, utilities and mining and quarrying.

We find that there are two key parameters that determine whether robots take jobs from workers or whether they complement labour; the elasticity of substitution between robots and humans in production and the elasticity of demand for the final products produced by robots and labour combined. Simple estimates of the impact of robots on employment across industrial sectors do not show any consistent results. But when countries are distinguished by their innovation capabilities, as determined by international organizations, we find robust results. Countries with good innovation capabilities, such as the United States, Germany and the Nordics, increase their employment when robots are introduced, whereas countries with poor innovation capabilities, such as the Southern Europeans, use robots to replace labour. There are differences across industrial sectors, such as more substitutability in non-manufacturing and in the automotive sector than in electronics and elsewhere, but the overall message is clear. Robots are much friendlier to labour when the country has a good innovation environment than when it has a poor environment.

We speculate about the reasons for this divergence. We find anecdotal and some more formal evidence of a correlation between innovation capabilities and stakeholder objectives, including employees' interests. Also, the introduction of robots in a country with a better innovation environment would normally be associated with higher productivity growth and so with more exports. The association between robot-labour substitution and innovation capabilities seems to be robust enough to justify more research into these links.

1 Introduction

Recent advances in industrial robotics are making it possible to automate many production processes, especially in manufacturing. The question about their role in labour markets most frequently raised in the empirical literature is whether the new technologies are taking jobs away from workers; more formally, whether robots and human labour are substitutes or complements. In this paper we investigate the role played by the institutional structures of a country that are summarized in the country's "national innovation system" in the answer to this question.

A national innovation system is defined as the network of institutions, such as universities, industrial research units and other technical and scientific establishments, whose activities and interactions affect the rate and direction of technological change in the economy. It includes the areas of the economy that affect searching, exploring and learning, which are all critical activities for the acquisition and generation of knowledge.[1]

We view the introduction of robots in production as the adoption of a new capital good that might displace or complement labour, measured by hours of work. We show that as in the pioneering work of Douglas North (1990), or the more recent work by Daron Acemoglu and James Robinson (2012), the impact of the new technology depends on the institutional structure of the country. In estimates with data from fourteen industrial countries over the period 2006-2016, we find that although when we omit the innovation system of a country in our estimation the impact of robots on employment at the industrial level is either zero or very small negative, once the national innovation system is taken into account results change. Countries that rank low in their national innovation system substitute robots for human labour much more than countries that rank higher, which might even increase hours in the sectors that introduce them.

We organize our thoughts around a model that consists of a robot-using sector (essentially manufacturing) and a labour intensive one that does not use robots (services). The driving force for the introduction of more robots is the fall in their price, which is widely documented and which we take as exogenous.[2] Deriving the impact of such changes on industrial employment,

[1]Different aspects of this institutional structure are discussed by Christopher Freeman (1987), Bengt-Ake Lundvall (1992), Richard Nelson (1993), Richard Nelson and Sydney Winter (2002), the European Commission (2018) and the Organisation for Economic Cooperation and Development (OECD, 1997 and 1999).

[2]See for example, International Federation of Robotics (IFR, 2017) and Georg Graetz and Guy Michaels (2018). The underlying assumption is that the fall in the price of robots is due to improvements in their production technology, which we do not include in the

we find that if the production elasticity of substitution between labour and robots is larger than the final-demand elasticity of substitution between manufacturing and non-manufacturing goods, the introduction of robots reduces hours in the robot-using sector, increasing them in the labour-intensive sector. At first sight this ranking is plausible, given what we know about robot capabilities in production and the demand elasticity for manufacturing goods (see below for more discussion).

There are two channels in which the innovation environment of a country can reverse the elasticity ranking, and so imply complementarity between robots and labour. The first concerns the elasticity of substitution between labour and robots. Although technically robots can perform the tasks done by labour, and so in principle there can be a high elasticity of substitution between them, several contributions in the management literature point to complementarities between labour and robots (more generally, between labour and new technologies based on digitalization). We postpone discussion of this, with references, to section 3.

The second concerns the elasticity of substitution in the utility function, which underlies the price elasticity of demand for manufacturing goods. A country with a better innovation system than another will have higher manufacturing productivity, the sector that benefits most from innovation. Although in a closed economy the elasticity of substitution between manufacturing and non-manufacturing goods has been documented to be small (below 1), which accounts for the productivity-growth explanation of the decline of manufacturing employment and the growth of services (Rachel L. Ngai and Christopher A. Pissarides, 2007, Daron Acemoglu and Veronica Guerrieri, 2008), manufacturing goods account for most of international trade. As Kiminory Matsuyama (2009) has shown, relatively faster productivity growth shifts the comparative advantage in the production of manufactured goods in its favour. This has a positive impact on employment, which mitigates the negative closed-economy effect.

The level at which we do our empirical work is closest to the paper by Graetz and Michaels (2018) but we focus on a different question. Graetz and Michaels focused on industrial productivity in a set of industries and countries comparable to ours (although for a much earlier time period) and examined the impact of robots on it by regressing the difference between the 2007 and 1993 productivity levels on robot density (the ratio of robots to one million hours) and some other variables. They find a strong impact of robots on productivity, something that our model requires, but when they considered their impact on employment in an extension of their model they

model.

found that robotics do not influence it, except for a small impact on low-skill workers. We use annual observations beginning 2006, which give richer results for employment, and show that taking into account the national innovation system ties down a statistically strong impact of robots on employment.

Making use of a similar data set, Francesco Carbonero, Ekkehart Ernst and Enzo Weber (2018) find a small negative impact on industrial sectors in developed countries but a larger negative impact in emerging countries. Their findings can be given an interpretation that is consistent with ours. Emerging countries on average have poorer innovation structures than industrial countries, so they are more likely to use robots to substitute labour without complementary job creation.[3]

We use country-industry data from the International Federation of Robotics (IFR) and EU KLEMS to compute the number of robots per million working hours in the production sectors of the United States and thirteen European countries, between 2006 and 2016. In simple regressions of working hours on robot density (and some other variables) we find only a very small negative and imprecise impact of robot density on hours of work in manufacturing, and a stronger negative impact on the non-manufacturing sectors, which are very small users of robots. We subsequently extract from the World Economic Forum's *Global Competitiveness Report* (Klaus Schwab, 2017, and earlier versions) country-level measures of "innovation capacity," and re-estimate the relation between robot density and hours worked, by taking into account the impact of each country's national innovation system on the marginal effect of robots on hours. Our index of a country's national innovation system is the simple average of six scores for as many indicators: the availability of scientists and engineers, collaborations between universities and industry in R&D, government procurement of technology products, quality of scientific research institutions, company spending on R&D and capacity for innovation. The individual scores are compiled by the World Economic Forum from surveys of senior company executives.

Our results suggest that countries with a low value of the innovation index are characterized by a negative impact of robots on hours of work. The countries with the lowest index value in our sample are the three Southern European and the one East European countries that are part of our sample, and the ones with the highest index value are the nine Northern European countries and the United States. In OLS regressions we find that the net

[3] Another set of studies consider the impact of robotics on employment across regions, an issue that we do not address here. See Daron Acemoglu and Pasqual Retrepo (2020) for a study of the impact of robots in US commuting zones and Francesco Chiacchio, Georgios Petropoulos and Davis Pichler (2018) for local labour markets in the European Union. Both sets of authors find large negative effects on local employment.

elasticity of robot density on hours of work in Italy and Spain is about -0.07 whereas in Finland and the United Stares it is $+0.04$. The point at which the sign of the net elasticity switches from negative to positive is close to the average index value of the innovation index, with 5 of the 14 countries in our sample, which have a mid-range index value, estimated to have statistically insignificant elasticities.

These results are confirmed by two other indices of innovation performance, the *Global Innovation Index* (Cornell University, INSEAD and WIPO, 2019) and the European Union's *Summary Innovation Index* (European Commission, 2019). They are also confirmed when we disaggregate our index of innovation performance. Five of the six indicators that make up our index give significant and comparable results when tested individually, so our results are not driven by outliers in the indicators or by the aggregation method. We did a number of other robustness checks to our empirical estimates and we also estimated using three different sets of instruments to remove any biases due to the endogeneity of robot density, but the basic result of the influence of the innovation environment on robot-labour substitution did not change.

In these regressions all industries are restricted to have the same coefficients on robot density. Allowing the estimation to assign different values to each industry coefficient reveals important differences between the "low-tech" industries and the two classified as "high-tech" on the OECD definition, as well as between manufacturing and non-manufacturing sectors. Non-manufacturing sectors are less responsive to the innovation environment of a country than manufacturing sectors are, to the extent that robots substitute labour in all countries in our sample. Within manufacturing, electronics, which are also producers of robots, are much more responsive to the innovation environment of a country than other sectors, as we would expect. The biggest user of robots, transport equipment, is less responsive and reduces hours for each robot in all countries in the sample (although less so in the more innovative countries). Finally, we show by decomposing our index into its individual indicators, that although five of the six yield statistically significant results on their own, the impact of the innovation environment is more powerful when the six indicators are present together than when they are introduced individually. This indicates complementarities between the indicators that increase their impact when they are introduced together.

The rest of the paper is organized as follows. Section 2 describes our model that is used to organize our thoughts. Section 3 defines the innovation environment and discusses the channels by which it influences the robot-labour substitution. In section 4 we discuss our data and in section 5 we report our estimation results. Section 6 further tests the specification with a number of extensions and robustness checks.

2 A two-sector model with robots and labour

The objective of this section is to organize our empirical estimation by suggesting the links between employment and robots. In section 3 we discuss how these links are affected by a country's national innovation system. The empirical literature that calculates how many jobs robots could potentially replace usually lists tasks and examines whether robots have the capability of performing the tasks. The econometric literature has followed a similar approach and modelled the adoption of robots as the profit-maximizing choice between humans and robots in the performance of a particular task.[4]

Here we follow a simpler and more conventional approach that brings out the main linkages that our research emphasizes. Our results depend on two elasticities, the elasticity of substitution of consumption goods in the utility function and the elasticity of substitution between robots and labour in the production function. The simplest model that illustrates our points is one consisting of two sectors. Sector 1 produces a consumption good that is tradeable and has a technology that can use both labour and robots and sector 2 uses only labour as an input and produces a consumption good that is not tradeable. We introduce a rudimentary foreign trade sector to illustrate the differences that it might make to the domestic results. Sector 1 can be identified with manufacturing, which is the sector that employs more than 99% of known robots. Sector 2 is the rest of the economy, which is dominated by services. We derive the equilibrium of this economy under the assumption that robots can be hired at a fixed and exogenous price ρ, expressed in wage units. Of course, in the data robots are traded manufacturing outputs but our static framework is not suited to the introduction of a robot production sector.

We consider a one-period model with production functions,

$$
\begin{aligned}
y_1 &= A_1 \left[(1-\beta)H_1^{(\sigma-1)/\sigma} + \beta R)^{(\sigma-1)/\sigma}\right]^{\sigma/(\sigma-1)} && (1)\\
&\equiv A_1 z && (2)\\
y_2 &= A_2 H_2 && (3)
\end{aligned}
$$

[4] On the former, see the pioneering work of Carl Frey and Michael Osborne (2017) and the many studies that followed, e.g., McKinsey Global Institute (2017), Ljubika Nedelkoska, and Glenda Quintini (2018) and Cecily Josten and Grace Lordan (2020). On empirical modelling see Daron Acemoglu and Pasquale Restrepo (2020) and Georg Graetz and Guy Michaels (2018). A notable early exception using more conventional techniques is Joseph Zeira (1998).

where y_i are outputs, H_i hours of work, R is the number of robots employed by sector 1, A_i are productivity parameters and β is the robot intensity of sector 1, $0 < \beta < 1$.

Output prices are given by p_i and they clear markets. There is free movement of labour so there is a unique wage W which clears the labour market. All agents are price and wage takers, so the maximization conditions for the three inputs satisfy the marginal productivity conditions,

$$p_1 A_1 (1-\beta) \left(\frac{z}{H_1}\right)^{1/\sigma} = W, \tag{4}$$

$$p_1 A_1 \beta \left(\frac{z}{R}\right)^{1/\sigma} = \rho W, \tag{5}$$

$$p_2 A_2 = W. \tag{6}$$

ρW in equation (5) is the (nominal) price of robots. The real (in wage units) price ρ is the parameter that drives the results of the model. In particular, we ask, what is the impact of a fall in ρ on equilibrium outcomes?

The domestic consumption levels of the two goods are given by $c_1 + c_1^*$ and c_2, where c_1^* denotes imports of manufacturing goods purchased at price p_1^*. Consumer income is Y, which is equal to the sum of the value of outputs of the two sectors. Domestic production of manufacturing goods is given by $c_1 + c_1^{**}$, where $c_1^{**} \geq 0$ denotes exports. The consumer maximization problem is

$$\max_{c_1, c_1^*, c_2} U(c) = \ln c \tag{7}$$

$$c = \left[\omega \tilde{c}_1^{(\varepsilon-1)/\varepsilon} + (1-\omega) c_2^{(\varepsilon-1)/\varepsilon}\right]^{\varepsilon/(\varepsilon-1)} \tag{8}$$

$$\tilde{c}_1 = \left[\psi c_1^{(\eta-1)/\eta} + (1-\psi) c_1^{*(\eta-1)/\eta}\right]^{\eta/(\eta-1)} \tag{9}$$

$$\sum_{i=1}^{2} p_i c_i + p_1^* c_1^* \leq Y. \tag{10}$$

The idea behind the nesting of the utility function is that there is a different elasticity of substitution between manufacturing and service goods, $\varepsilon \geq 0$, which is likely to be small, and a higher elasticity of substitution $\eta \geq 0$ between manufacturing goods produced at home and abroad. We assume $0 < \omega < 0$ and $0 < \psi \leq 1$, allowing for the case of the closed economy when $\psi = 1$.

Labour markets clear subject to the resource constraint,

$$\sum_{i=1}^{2} H_i \leq 1, \tag{11}$$

whereas output markets clear according to

$$\begin{aligned} c_1 + c_1^{**} &\leq y_1 & (12) \\ c_2 &\leq y_2 & (13) \\ Y &= p_1 y_1 + p_2 y_2, & (14) \end{aligned}$$

given an exogenous demand for exports, c_1^{**}.

Definition *Equilibrium is defined by an allocation for consumption goods that satisfies the consumer maximization problem (7)-(10) and market clearing conditions (12)-(14), subject to exogenous foreign prices* p_1^* *and demand for exports* c_1^{**}*, a labour allocation that satisfies the profit-maximizing conditions (4) and (6) and resource constraint (11), and a robot input that satisfies the profit-maximizing condition (5) subject to an exogenous real price* ρ*, measured in wage units*

We state here the main results of the model in the form of two propositions and collect all derivations and proofs in the Appendix.

Proposition 1 *Lower real robot price* ρ *raises the robot density of sector 1 (the ratio of robots to hours of work) and the productivity of sector 1* (y_1/H_1)*, and lowers relative price* (p_1/p_2)*. These results are independent of foreign prices and exports so they hold in both closed and open economies.*

The intuition behind these results is that lower robot price is equivalent to a technological improvement that benefits the robot-using sector. In a more complete model the lower price of robots would be due to technological improvements in the robot-producing sector of the economy, so it is an example of a technological improvement in an intermediate goods sector that transfers to the firms that use the intermediate good (the robots) as an input. The results of Proposition 1 have been the focus of the empirical work of Graetz and Michaels (2018) and we will not test them further.

Proposition 2 *In the closed economy lower robot price* ρ *raises hours of work in the robot using sector if* $\varepsilon > \sigma$*, it has no impact on hours if* $\varepsilon = \sigma$ *and shifts hours from sector 1 to sector 2 if* $\varepsilon < \sigma$*. With international trade, the condition* $\partial(p_1/p_1^*)/\partial\rho \leq 0$ *is sufficient for two further results. First, for given exports, lower robot price has a positive additional impact on hours in the robot-using sector if* $\eta > \varepsilon$*, has no additional impact if* $\eta = \varepsilon$ *and has a negative additional impact if* $\eta < \varepsilon$*. Second, lower robot price has a further positive impact on hours in sector 1 through a bigger volume of exports.*

The results for the closed economy are a generalization to a CES production function of the results in the structural transformation literature. A fall in the price of robots is a technological improvement in sector 1 that raises its output, reduces its relative price and increases its relative demand with elasticity ε. If the elasticity of demand is low ($\varepsilon < \sigma$) the rise in demand is not enough to absorb the additional output so labour has to leave the sector to restore equilibrium.

For the open economy the stated sufficient condition is that the fall in the price of robots deteriorates the country's terms of trade. A mechanism for this effect is that the country in question is able to use robots more effectively to reduce the unit production cost of manufacturing goods than its trading partners can. We are going to argue that this effect is likely to obtain when the domestic country has a better innovation environment. The terms of trade change makes domestic residents substitute domestic goods for imports. If the rise in domestic demand due to this channel is bigger than the general rise in domestic demand ($\eta > \varepsilon$) there is need of an increase in hours in sector 1 over and above any closed-economy adjustments. The property $\eta > \varepsilon$ is easily justified in our model, as ε is the elasticity of substitution between services and manufacturing, whereas η is the elasticity of substitution between differentiated manufacturing goods.

Finally, by making the common terms-of-trade assumption of the open economy literature, that a fall in the relative price of domestic to foreign manufacturing leads to a rise in the demand for exports, we obtain another positive influence on domestic manufacturing employment through an increase in export demand.

It follows from Proposition 2 that the introduction of international trade to a closed economy model introduces ambiguities about the direction of employment change following the introduction of robots in production, that parallel the impact of other more general technological improvements (Kiminori Matsuyama, 2009). The closed economy result shows that robots do not always "destroy jobs". They do only when they are a sufficiently good substitute for labour ($\sigma > \varepsilon$). But in the structural transformation literature the requirement of a small ε is needed and it is generally assumed, so on the face of it the introduction of robots must reduce hours of work in manufacturing. For aggregates such as total manufacturing and services, a plausible range for ε is 0 to 0.3 (see Rachel Ngai and Christopher Pissarides, 2008). In the open economy the negative impact on manufacturing hours could be reversed if the introduction of the robots reduces the domestic price by more than the fall in the price in foreign countries. Of course, worldwide the closed economy result holds and $\sigma > \varepsilon$ is a sufficient condition for the reduction of global manufacturing employment.

3 The innovation environment

Our model points to three elasticities of critical importance in signing the impact of robots on employment, σ, ε and η. We now argue that the innovation environment of a country will influence firms' responses to the robotics technology through two channels. They respectively influence the elasticity of substitution between robots and workers, σ, and the elasticity of demand for manufacturing goods, which is a weighted average of ε, the low elasticity of domestic demand, and η, the higher elasticity of foreign demand.

We summarize evidence here that supports these claims. The first is related to company objectives beyond profit maximization; firms pay attention to other objectives as well, such as stakeholders' interests. We discuss evidence that supports the claim that there is a connection between the innovation environment and these other objectives, which may lead firms to choose production technologies that involve less substitution between robots and labour. The second is related to international trade and exports of manufactured goods. Countries with more innovation capabilities are likely to have higher manufacturing productivity and export a higher fraction of their output, other things equal. The overall demand elasticity for their manufacturing goods attaches more weight to the η elasticity and less to the ε elasticity than in countries with lower innovation capabilities.

In order to discuss this evidence further, we first define more precisely our concept of innovation environment and describe the data that we used to construct our innovation index. We used the innovation capabilities pillar (no. 12) of the World Economic Forum's *Global Competitiveness Report*, which has been available in its current form since 2006. Up to the 2017-2018 *Global Competitiveness Report* the innovation capabilities pillar was computed in comparable format and it was the average of seven indicators: capacity for innovation; quality of scientific research institutions; company spending on R&D; university-industry collaboration in R&D; government procurement of advanced technology products; the availability of scientists and engineers; and patent applications (see Klaus Schwab, 2019, 323). The main input to the index is the annual Executive Opinion Survey, which records the opinions of business leaders about the indicators that make up the index, except for patent applications. The first six indicators derived from the Survey are based on the subjective responses of the business people and expressed as scores on a scale of 1–7, with 7 being the most favourable (for innovations) outcome. For patents the World Economic Forum takes the number of applications filed under the Patent Cooperation Treaty (PCT) and normalizes it to a scale of 1-7 to align it with the results of the Executive Opinion Survey. The way of counting patents, however, changed during the years of the sample and it was not possible to go back and adjust the earlier numbers on the basis of the new counting method. Partly because of this change, partly because the patent indicator is based on a different collection method from the other six, we computed our innovation index by excluding patents and setting it equal to the average score of the first six indicators.[5]

Returning now to the properties summarized in Proposition 2, the task-based literature shows that robots could do a lot of tasks that humans do, so the elasticity of substitution σ is potentially very high. But it does not necessarily follow that all employers will find it profitable to use robots in that capacity; in particular that all employers will choose a production technology with high σ. A large recent literature on corporate objectives argues that companies have objectives beyond profit maximization. In particular that they take into account stakeholders' objectives, including those of employees.

The case for maximizing shareholder value was most influentially put forward by Milton Friedman (1962) in his book *Capitalism and Freedom* and subsequently in a widely discussed article in the *New York Times* magazine. More recently, it has been criticized as an inadequate objective by a large management literature.[6] Many quotes that confirm this change are found in the literature. A recent example from a company that uses a large number of robots in its operations is due to Amazon's "chief robotics technologist," who told the British Broadcasting Corporation (BBC), in response to the company's expanding use of robots in its warehouses, "The way that I think about this is a symphony of humans and machines working together, you need both. The challenge that we have in front of us is how do we smartly design our machines to extend human capability?"[7] Another influential statement was made by the Chairman and Chief Executive of Blackrock, the biggest asset management company in the world, who in a letter in January 2018 to the CEOs of the companies whose assets made up the Blackrock portfolio, he urged them to "be deliberate and committed to embracing purpose and serving all stakeholders – your shareholders, customers, employees."[8] Concern for employees as stakeholders is also observed in the regular survey of compa-

[5] We repeated all our regressions with the average value for pillar 12 given by the World Economic Forum and results were comparable throughout, with small changes in point estimates only. The disaggregated regression with patent numbers only, comparable to those in Table 7 below, gave completely insignificant results.

[6] See *New York Times Magazine,* September 13,1970 for Friedman's article and Edward Freeman (2010) for the stakeholder approach. For a more recent critique of Friedman's doctrine see Colin Mayer (2008) and (e.g.) the University of Chicago commentary in this link https://review.chicagobooth.edu/economics/2017/article/it-s-time-rethink-milton-friedman-s-shareholder-value-argument

[7] https://www.bbc.co.uk/news/technology-48590628 11 June 2019.

[8] https://www.blackrock.com/corporate/investor-relations/larry-fink-ceo-letter

nies by the McKinsey Global Institute, in which the differential response to the new technology by different companies (some using it to substitute labour, others using it to expand business and improve working conditions for employees), is something that is regularly observed.[9]

The argument in this literature is that in many cases robots can be a complement to labour; in terms of the model, that if there is a choice of technology, companies, with other objectives in mind, will choose production processes for which the elasticity σ is a small number.

Our argument that a country's innovation environment influences the robot-hours substitution requires also that there is an association between stakeholder objectives and the innovation environment. There is no direct evidence for this (or against it) but there is ample indirect evidence. All indices of innovation performance pay particular attention to the quality of human capital and the availability of good education and training systems. Of the available innovation indices the *Global Innovation Index* gives more details of its construction and includes measures for "information about the degree of sophistication of the local human capital currently employed" as well as "the conception or creation of new knowledge, products, processes, methods and systems, including business management." (see below, section 6.3, for more details). Better qualified and more sophisticated human capital is less likely to be substituted by robots than less well-trained human capital (see for example, International Federation of Robotics, 2018, and Konstantinos Pouliakas, 2018).[10]

Another type of evidence also points to a link between the innovation environment and employee-focused policies: diversity. A company has diversity when it employs a labour force, especially at decision-making level, that contains a mix of people that reflects society, across gender, ethnic and social origin, career path, sexual orientation and educational and industry background. Diversity is a stakeholder objective taken into account by companies that do not focus solely on profit maximization. We cite two recent studies that find a link between diversity and innovation.

In a survey of 1,700 companies in eight countries conducted in 2018, the Boston Consulting Group found strong evidence that more diverse companies

[9] See McKinsey Global Institute (2018, 2019), Jacques Bughin et al. (2019) and Meera Sampath and Pramod Khargonekar (2018). Of course, not all employers behave in this way. For example, Foxconn, the Chinese conglomerate that manufactures smartphones, declared its intention to replace most of its employees by robots as far back as 2011, and has been pursuing this policy ever since.

[10] Both these references go further and suggest that robots complement better trained human capital, reaching the conclusion that lifelong learning and upskilling can lead to complementarity between hours and robots.

were more innovative, more likely to be adopting digital technologies and to be following policies that paid attention to the interests of employees as stakeholders. In their survey respondents were asked to rank the factors that enabled a more inclusive environment and ranked "managers value employee contributions" as number one.[11]

In 2019 the London *Financial Times* published for the first time a ranking of "Diversity Leaders". Seven hundred companies were ranked on the basis of their "gender balance, openness to all forms of sexual orientation, disability as well as an ethnic and social mix that reflects wider society."[12] There are eight countries in our sample that are also included in the *Financial Times* sample.[13] We extracted the number of companies in each of the eight countries that feature in the top 100 companies (results with the top 200, 300 and 500 companies were very similar) and correlated them with our innovation index, after rescaling by dividing the number of companies in each country by the total number of registered enterprises given by Eurostat (adjusted to have mean 1, so the mean value of the adjusted company series is the same as the actual number). The result is shown in Fig. 1.

The simple correlation coefficient between the innovation index and the log of the number of diverse companies is 0.66. A surprising result in these eight countries is Sweden, given its record of a large welfare state intended to reduce inequalities and increase inclusiveness, which is generally regarded as successful. In the *Financial Times* index it is listed as a country with relatively very few diverse companies. As the survey was conducted in only one year we cannot compare across years for consistency. But if Sweden is dropped from the sample, the simple correlation coefficient with the remaining seven countries rises to 0.93. We conclude that as in the Boston study, this evidence points to a strong correlation between the innovative environment of a country and the diversity of its companies.

The open economy provides another channel that explains a differential response of manufacturing employment to new technology across countries. It is clear from the data that employment shares in manufacturing in some countries cannot be easily explained solely by the dynamics of structural

[11] Several other reports by this group and others make similar claims. See https://www.bcg.com/en-us/publications/2018/how-diverse-leadership-teams-boost-innovation.aspx for the results of the survey and more discussion.

[12] The main source of information for the ranking is a survey of 80,000 employees working in 10,000 companies employing more than 250 people, in ten European countries. See *Financial Times,* November 13, 2019, "Striving for Inclusion, Top European Companies Ranked" https://www.ft.com/content/bd1b4158-09a7-11ea-bb52-34c8d9dc6d84 It is intended to make the survey annual.

[13] Austria, Belgium, France, Germany, Italy, Netherlands, United Kingdom and Sweden.

change in closed economies.[14] Foreign trade plays a role, a connection that is even more obvious than in the European comparisons in countries like Japan and South Korea in the second half of the 20th century and China in the first two decades of this century.

The link between the innovation index and the trade performance of a country has two components. The first is the one summarized in our Proposition 1 and documented by Graetz and Michaels (2018). Countries that adopt more robots increase their productivity and this gives them an advantage in international markets. The second is more general and it is the one that motivated Matsuyama's (2008) study. Firms in countries that rank higher in the innovation index do more R&D (by the definition of the innovation index) and produce more advanced technology products. They are therefore likely to achieve higher average levels of productivity growth than firms in countries with lower rank in the index (higher A_1 in the notation of our model, and since most of the R&D is in manufacturing sectors, higher A_1/A_2). From equation (24) in the Appendix this gives a lower relative manufacturing price in the more innovative country, and so it gives it a comparative advantage in international markets.

Proposition 2 shows that a comparative advantage in manufacturing leads to a positive impact on manufacturing employment through more exports. Countries with a high innovation score should have a positive open-economy impact on hours of work when more robots are introduced, in contrast to lower-ranking countries which do not have the comparative advantage. These impacts are superimposed on any closed economy effects, with theoretically ambiguous overall results.

These arguments show that despite the frequent claims that robots are taking jobs away from labour, there could be circumstances in which robots either complement labour or give a boost to employment by reducing the relative price of manufacturing goods. Our claim is that these circumstances are more likely to arise in countries with more advanced innovation systems. Ultimately the extent to which robots and workers substitute or complement each other can only be discovered empirically; we now turn to this question.

4 The data

Our data are annual observations of robot use and hours of work across industrial sectors and countries. We have already discussed our definitions

[14]For example, in three very similar European countries, Germany, France and the United Kingdom, manufacturing shares of hours of work in 1995 were, respectively (in percent), 21.4, 15.0 and 17.0. In 2017 they became 18.3, 9.5 and 8.8.

and sources for national innovation systems.[15] We mention one more thing about it here. The annual score computed by the World Economic Forum changes very little, if at all, from year to year, and there are some missing observations. We run our regressions both with the annual series and with the sample average for each country, as a single index. Results were virtually identical, indicating that the estimates are driven by the differences in the index across countries and not by within-country variations. The regression results that we report here are with the annual series, which use all available information.

The source that we use for the number of productive robots in employment is the International Federation of Robotics (https://ifr.org), and the source for the labour market variables is the 2019 update of EU KLEMS (Robert Stehrer et al. 2019). Our sample is 2006-2016, the earliest year for which we have complete data sets for industrial robots and the innovation index, and the most recent year of the EU KLEMS data. We focus mainly on seven manufacturing sectors but we also include three non-manufacturing sectors. We have sufficient data from fourteen industrial countries with some missing observations, especially in the early years. The list of countries and sectors, with sample means, are shown in Tables 1 and 2.[16]

The IFR defines industrial robots as fully autonomous machines that can be programmed to perform several manual tasks without human intervention. These tasks include handling, welding, dispensing, processing, assembling and dismantling. The data are collected from deliveries by the suppliers of manufactured robots. They are adjusted by the IFR for depreciation by assuming that the average service life of a robot is 12 years and that there is an immediate withdrawal of the robot after this time (IFR, 2017).[17]

Our employment variable is hours of work in each sector and country. We also obtain data for wages, the total capital stock and ICT capital. We convert nominal variables to 2010 US dollar prices using purchasing power parity (PPP) exchange rates.

The IFR uses the International Standard Industrial Classification (ISIC) for industries, whereas EU KLEMS uses the General Industrial Classification of Economic Activities (NACE). We matched the two sources by allocating the original nineteen ISIC Rev.4 industries from the IFR to the NACE Rev.2 industries. We were able to match most sectors one for one but the data for

[15] The Appendix gives more details on sources and the construction of variables.

[16] Initially we also included construction in our sample but results were poor. It is a large sector, its average hours being about 70% of average manufacturing hours, but a very small user of robots. Its average robot number in our sample was 0.16% of the number of manufacturing robots (one sixth of 1%).

[17] When countries calculate their own operational stock the IFR uses that figure instead.

chemicals and rubber, and plastics and other non-metallic mineral products, are not reported separately in the IFR dataset. We aggregated these industries in EU KLEMS, together with coke and refined petroleum products, into the plastics and chemical products category. Finally, we excluded from our analysis the residual categories "all other non-manufacturing sectors" and "all unspecified sectors". These categories account for about 15% of robot deliveries.

In Table 1 four countries stand out as having the lowest index values for innovation, Greece, Italy, Spain and the Czech Republic (Czechia), with a gap between them and the rest. These are the only countries that we have outside the United States and North-Western Europe. At the more innovative end progression is smoother, although the next six countries could be described as middling and the remaining four as the innovation leaders, which contains Germany, Sweden, Finland and the United States. The mean value of the index is 4.63, with only the four weakest countries below it and the rest above it. There are also large differences in robot density, both across countries and industries. Perhaps a surprising result is that there is no correlation at all between a country's innovation score and robot density. Italy, for example, is one of the biggest robot users, although it has the second lowest value for innovation capacity. Given the relatively high robot density in the manufacture of transport equipment (Table 2), there is some correlation between industrial structure and country robot density, with Germany, Italy and France having high densities and a relatively large automotive sector. But robot density is also high in Denmark and Finland, which do not produce cars. Greece is an outlier as a very low user of robots and its relatively high value in the non-manufacturing sectors is due to a relatively high value in mining and quarrying.

5 Empirical model: The basic equation estimates

Our empirical strategy is to estimate log-linearized semi-reduced form equations for annual hours worked in production industries in terms of robot density, the index for the innovation system of the country and a number of other labour market variables:

$$\ln H_{ict} = \beta_0 + \beta_1 \ln(R_{ict}/H_{ict}) + \beta_2 \ln(R_{ict}/H_{ict}) * V_{ct} + Z_{ict} + \varepsilon_{ict} \qquad (15)$$

H_{ict} is the number of annual hours worked in millions, R_{ict} is the number of robots in production, each distinguished by industry i, country c and year t, and V_{ct} is the innovation index for each country. The vector Z_{ict} represents other control variables: hourly wages, the capital stock, the ratio of ICT capital to the total and industry, country and year fixed effects; ε_{ict} is the error term.[18]

A key claim of our model is that country hours respond differently to the introduction of robots in production, depending on their innovation environment. Countries with a more favourable national innovation system are in a position to either mitigate or reverse any negative impact that the introduction of robots might have on hours of work. The elasticity with which hours of work respond to an increase in robot density is $\beta_1 + \beta_2 V_{ct}$ and we expect the sign of the estimated β_1 to be negative but that of β_2 to be positive.

We estimate equation (15) for manufacturing and for the full sample that includes the three non-manufacturing sectors. We estimate it with OLS as well as with instruments that deal with any endogeneity bias in robot density. We also explore further the role of the innovation environment by estimating it with available alternative measures and by breaking down the innovation system into its component parts and estimating the impact of each, to test for any big differences between them. Some other robustness tests are performed and reported in the section that follows.

Table 3 shows the results of the estimation of the basic equation (15) for the seven manufacturing sectors. Country and year fixed effects are included. Consider first results for the simple regression without taking into account the innovation system of the country. In column (1), the impact of robot density on hours of work is negative but weak. In addition to robot density and the fixed effects we include three other economic variables, the capital stock, the fraction of the capital stock classified by EU KLEMS as ICT and the total wage bill for the industrial sector divided by hours of work. The elasticities of the three economic variables are estimated precisely and the point estimates are plausible. These estimates are robust to differences in the specification of the equation; the capital elasticity is 0.72, ICT capital contributes positively another 0.1 to the elasticity (ICT_{ict} is already included in K_{ict}), and the hourly wage elasticity is -0.3.

In column (3) we estimate the equation with 2SLS using our preferred instrument, robot density in the Republic of Korea. The idea of the instrument is to isolate the impact of technological improvements in the manufacture of robots. We have chosen Korea as it is sufficiently removed from our sample of Europe and the United States, so other common influences are remote,

[18] Because we always estimate the regression with country fixed effects, a linear term in V_{ct} is redundant, given what we said about the cross-country and within-country variation in it.

and it is the country of the largest robot densities in manufacturing worldwide. The results of the IV regression show that the negative impact of robot density on hours in the absence of the innovation environment is not robust to instrumentation.

So overall, the conclusion from the estimation of equation (15) for manufacturing, under the restriction $\beta_2 = 0$, is that although there is small negative impact of robot density on hours of work, it is not precise or robust across estimation specifications. In contrast, the impact of other economic variables on hours of work is estimated precisely and with robustness.

This contrasts sharply with the results of estimating the regression by taking into account each country's national innovation system. In column (2) of Table 3 we show OLS estimates, in which the elasticity on robot density is precisely estimated to be -0.34. This negative estimate contrasts with a positive estimate on the interaction of robot density with our index of the national innovation index, estimated to be 0.07. Dividing the former by the latter gives the point at which the net effect switches sign from negative to positive, and this is at $V^0 = 4.93$, which is slightly above the mid point (4.63) of the innovation index. Calculated at the sample mean for V_{ct}, the range of the net elasticities across countries is from -0.105 for Greece and -0.078 for Italy to $+0.04$ for Finland and the United States.

The instrumental variables estimation of the regression with the innovation index is in column (4) of Table 3. The results confirm an even stronger influence of the innovation index on the impact of robots on hours. Both estimated coefficients on the endogenous robot density rise in absolute number, from -0.34 in the OLS estimate to -0.54 in the IV estimate, and from $+0.07$ to $+0.115$. The net impact of robots is now zero at $V^0 = 4.68$, closer to the mean, and the net elasticities vary from -0.15 in Greece to $+0.095$ in the United States.

In Table 4 we calculated the net elasticities at sample means implied by the OLS estimate for all countries, with their robust standard errors. In the four countries with the weakest innovation systems (three Southern European and one East European) the net elasticity is precisely estimated with a negative sign. These countries are joined by Austria with a weaker negative elasticity. The four most innovative countries (the United States and three Northern European countries) all have strong and significant positive elasticities. The other countries have no significant elasticity estimates.

In order to give more information on the quantitative importance of these estimates we calculated an approximation to the implied change in annual hours when one more robot is introduced. From (15) we get, for a given initial value for H_{ict},

$$\Delta H_{ict} = (\beta_1 + \beta_2 V_{ct}) \frac{H_{ict}}{R_{ict}} \Delta R_{ict}, \tag{16}$$

where $(\beta_1 + \beta_2 V_{ct})$ is the net coefficient shown in Table 4 for each country and H_{ict}/R_{ict} is the inverse of robot density for each country. We compute the change in hours from (16) for $\Delta R_{ict} = 1$, at the average value of the innovation index and the average robot density of the last five years of the sample (i.e., for 2012-16). The result is shown in Table 4 under the heading ΔH per robot.

Overall the results appear plausible, with the impact ranging from substantial negative in Italy and Spain to substantial positive in the Nordic countries and the United States. Results appear implausible for Greece, which has very small average densities and missing observations.[19] Translating from annual hours to jobs, at average hours per manufacturing job, the impact of one more robot in Italy is -4.72 jobs, very similar to Spain's, whereas in Germany it is $+0.98$ and in the United States and Finland $+2.62$ jobs.

6 Extensions and robustness checks

6.1 Alternative instruments and fixed effects

To test further the robustness of the basic equation estimate, we estimated the same equation with two alternative instruments, robot density in Germany from 1993 to 2004 and patents in Korea normalized by population. The justification is the same as with our preferred instrument. Germany is the country in our sample which had the biggest penetration of robots in its manufacturing and has good data going back to 1993. Since the price of robots has been falling long before our sample begins (IFR, 2017), any correlations between the German trends before 2004 and our sample are likely to be due to technology improvements in robot production, as reflected in their price. Our third instrument, patents in Korea, is another signal of technology trends in the country with most robot penetration in the world.

Results with these instruments were similar to each other. Without the innovation index, the estimate of the impact of robot density on hours became stronger in the regression without industry dummies, with elasticities

[19] Despite this we retained Greece in the sample but tested whether our estimates were affected by its inclusion (and also by the inclusion of Czechia) but they were not. In our discussion of country comparisons we refer to Italy or Spain as the countries with the weakest national innovation systems, rather than Greece, because of the data problems with Greece.

-0.036 and -0.054 respectively, but it became completely insignificant when industry dummies were introduced. In the regression with the innovation index the estimates with the other two instruments were very similar to the IV estimation in Table 3. As before, instrumentation of the regression with the innovation index shows more robustness than in the one without the index, confirming the point estimates in Table 3.

The results reported so far introduce country and time fixed effects but not industry effects. We repeated the estimation with a full set of industry dummies for the seven sectors and results were of the same order of magnitude as in the regressions without industry dummies. Under the restriction $\beta_2 = 0$ the estimate of the coefficient on robot density in the OLS regression was -0.038 (s.e. 0.009) but in the IV estimation it became $+0.11$ (s.e. 0.25). The three estimated coefficients on the other economic variables were very similar to the ones in Table 3. We tried two other specifications, two-way clustering with 98 country/industry clusters, and three pairwise interactions of the dummies, country/industry, country/years and industry/years. In both cases the results were very close to the ones in Table 3. In the two-way clustering the coefficient on robot density was completely insignificant whereas in the case of interactions of fixed effects it became negative but not strong.[20]

IV estimation in the regression that included the innovation index was also robust to the alternative specifications that we tried. With industry dummies the coefficients were close to the ones without, with the negative elasticity on robot density estimated to be -0.331 (s.e. 0.032) and the estimate on the interaction term $+0.062$ (s.e. 0.007). Two-way clustering also gave similar results, with coefficients given by -0.538 and $+0.115$ respectively and significant at the 1% level. The IV regression with country and industry interaction gave estimates -0.510 and $+0.109$, again significant at the 1% level. The only failure in the estimation was the IV estimation of the other two dummy interactions, for which our estimation did not converge.

6.2 Sample exclusions

With seven industrial sectors and fourteen countries, mostly small European ones, it is possible that single important sectors or countries drive the results. We checked whether the two most prominent users of robots in each case, Germany and transport equipment (see Tables 1-2), are responsible for our estimates. The answer is that they are not. The exclusion of Germany

[20]The full estimation results with the alternative specifications can be made available on request

makes virtually no difference to the estimated coefficients in Table 3. This is consistent with the fact that Germany is fairly close to the mean of the innovation index distribution, where the impact of robots on hours of work is small (Table 4). The exclusion of the transport sector does not affect the performance of the equation but it reduces the implied substitutability between labour and robots. Without transport equipment Italy has net elasticity of -0.05, instead of -0.08 as in Table 4, whereas the United States and Finland have elasticity $+0.095$ instead of $+0.04$ for the full sample. The lower substitutability outside transport equipment is consistent with the results discussed in sub-section 6.4, about the differences in estimates across sectors.

6.3 Alternative measures of innovation performance

There are two other widely-available measures of a country's innovation environment, the *Global Innovation Index* and the *Summary Innovation Index* of the *European Innovation Scoreboard*. The Global Innovation Index has been published since 2007 by Cornell University, INSEAD and the World Intellectual Property Organization (WIPO) and is the average of scores in two sub-indices, the Innovation Input Sub-Index and Innovation Output Sub-Index (see the latest edition, Cornell University, INSEAD and WIPO, 2019, especially Appendix 1). The innovation input sub-index consists of five pillars which capture the country's enabling environment for innovation. The innovation output sub-index is the average of two pillars that capture the outputs of the innovation activities within the country. The overall index is the average of the two sub-indices. The five pillars of the input index are the quality of institutions, human capital, infrastructure, market sophistication and business sophistication, and the two pillars of the output index are knowledge and technology outputs and "creative" outputs. The data sources are all secondary published sources, mostly by international organizations such as the OECD and Eurostat.

The Summary Index of the European Commission Scoreboard is an unweighted average of several indicators (see European Commission, 2019). Currently the number is 27, but in earlier years there were fewer. In the years of our sample they were divided into three categories, enablers, including factors like education standards and availability of venture capital, firm activities, such as R&D and patent applications, and outputs, such as employment in knowledge-intensive industries and exports of high-tech products. The data sources are again publications of international organizations such as Eurostat, OECD and the United Nations. The index covers all members of the European Union and in the early years of our sample it covered the United States as well, although inclusion of the United States has now been discontinued.

The simple correlation coefficient of our index with the Global Innovation Index is 0.94 and with the European index (excluding the United States) also 0.94 (the correlation between them is 0.89). The ranking of countries is also very close to each other in the three indices. Not surprisingly, given the high correlation between the three indices, the estimation results with the two new indices are very similar to the ones in columns (2) and (4) of Table 3. In the interests of space we do not report the whole estimated regressions but report here only the two key coefficients, for the log of robot density and the same interacted by the new innovation index.[21]

For the Global Innovation Index, which has range 0 to 100, the estimated coefficient on robot density is -0.398 (s.e. 0.041) and for the interaction term 0.007 (s.e. 0.001). For a country close to the mean of the index, like France, the net effect of robots is very close to zero, whereas for Italy and the United States the net elasticity of robot density on hours of work is -0.07 and $+0.04$, respectively, which are very close to the estimates in Tables 3 and 4. For the EU summary index, which has range 0 to 1, the coefficient estimate on robot density is -0.248 (s.e. 0.025) and for the interaction term the estimate is 0.449 (s.e. 0.048). The implied net elasticity for Italy is -0.08 and for Sweden, which in the absence of the United States is the most innovative country in this index, it is $+0.06$.

It is clear that our estimates can be replicated with alternative indices for a country's innovation environment and they are not due to peculiarities in our index. The main difference between our index and the two alternatives is that the latter two use data published by international organizations whereas the source of data for our index is a survey of firms conducted by the World Economic Forum. In both cases the correlation between our index and the alternatives is extremely high and the estimated elasticities are very close to each other in all three cases. We continue with our index only, which gives more complete data information for our sample.

6.4 Industry breakdowns

So far we have restricted ourselves to manufacturing industries, which are the main users of robots. We now investigate the impact of robots with two alternative samples, one that treats transport equipment and electronics separately from the rest of manufacturing and one that includes three

[21] The results shown are for the OLS estimate without industry fixed effects. Results are very similar if instruments are used and if industry fixed effects are included.

non-manufacturing sectors which are robot users, albeit at a much lower rate than manufacturing (see Table 2). Transport equipment and electronics are defined by the OECD as high-tech and both are heavy users of robots; electronics is a producer as well as user of robots whereas transport equipment is by far the biggest user of robots. The other five sectors are low-tech except for some elements of our chemicals sector, which cannot be separated out. We refer to their aggregate as low-tech. Table 5 shows the results of the estimation when the two hi-tech sectors are estimated separately.

The estimation gives good statistical results, with all estimates significant at the 5% level. We introduced industry dummies for the two industries in the regression and for the aggregate of the rest of manufacturing, but results were virtually identical to the ones without dummies. Results are in line with the aggregate manufacturing estimates, with the replacement of labour by robots in the countries with better innovation performance weaker or completely reversed. The estimates for the non-tech sectors are close to the aggregate manufacturing ones. The point at which the sign of the net effect of the impact of robot density on hours reverses is 4.64 (instead of 4.93 for the aggregate), with both close to the mean index of 4.63. The elasticity estimates for Italy and the United States, however, show a bigger range than the ones for the aggregate, -0.083 and $+0.084$ respectively (see Table 4 for the aggregates).

We highlight two differences for electronics and transport equipment, when compared with the aggregate. First, in electronics the innovation environment plays a more significant role than in other sectors and there is overall less substitution of robots for labour. The point at which the sign of the net impact of robot density on hours switches is lower, at 3.94, and all net elasticities shift to the right. The elasticity for Italy in this sector is -0.016 and in the United States it is $+0.16$. This is easily justified. Electronics is technologically the most advanced sector and it is a producer of new technologies (including robotics) as well as a user. So it benefits a lot more from a favourable innovative environment than other sectors do.

In contrast to electronics, the transport equipment industry is not very sensitive to the innovation environment. The impact of robot density on hours of work is negative in practically all countries, with an estimated elasticity of -0.05 in Italy and zero in the United States. This sector is an outlier in the use of robots and indeed the possibility of assembling cars with robots was a major impetus to the development of robot technology, so it is not surprising that the large use of robots does not create jobs on top. A favourable innovation environment in the country still saves some jobs from replacement by robots in this sector, but it does not induce additional job creation.

6.5 Non-manufacturing industries

Table 6 shows the results of estimation when we add three non-manufacturing production sectors to the sample, agriculture, mining and quarrying and water supply, gas and electricity (utilities). These three sectors are small users of robots and there are several zero entries for robot density in some countries, which we classify as missing observations. We use industry fixed effects for the non-manufacturing sectors and a common one for manufacturing, although the results are virtually identical with a full set of manufacturing fixed effects.

The striking result in this table is the difference between manufacturing on the one hand and non-manufacturing on the other. The manufacturing estimates are very similar to the ones in Table 3, with the more innovative countries creating jobs when robots are installed. In contrast, the non-manufacturing results indicate that there is a substitution of robots for labour in all countries. Although the innovation environment still has a small, statistically significant effect on the net elasticity, the biggest net impact, in the case of the United States, is still a significant negative number at -0.055. For the biggest country with a poor innovation environment, Italy, the net elasticity is -0.087. For these industries, even a country with the maximum innovation environment score, 7, yields a negative net elasticity. Considering that the three sectors are agriculture, mining and utilities, it appears that the use of robots is almost exclusively for the automation of processes done by humans, such as moving boxes or digging the ground, without a complementary job creation.

6.6 Decomposing the innovation index

Our final robustness test is a very stringent one that breaks up the innovation index into its six components and runs the OLS regression in column (1) of Table 3 again, with each replacing the national innovation index. It is stringent because our innovation index might average out any fluctuations in a single index, which will influence the estimation in this decomposition. The estimates of the two main coefficients, as well as the value of the component's index that gives a zero net impact of robot density on hours, are in Table 7.

All indicators except for the availability of scientists and engineers give statistically significant results that conform to the estimates of Table 3. Two of the indicators, R&D spending and government procurement of tech products, are flow concepts, whereas the others are closer to institutional features, yet there is no discernible difference between them in the estimation. The only difference between the disaggregate results and the aggregate ones is that the point of the index at which the sign reverses from negative to positive is higher for the individual indices than for the aggregate. This might indicate some complementarity between the individual indicators. Any one indicator alone is not strong enough to reverse the negative impact of robots on hours but all together are sufficiently strong to do it for about half the countries. This is indicative of a powerful result that needs further research: the existence of complementarities between different aspects of the innovation environment that reinforce each other when they are present together.

7 Conclusions

Our argument in this paper is that robots have the technical capabilities to replace humans in manufacturing and some other sectors, but whether they do or not depends also on the institutional environment of the country and the incentives that firms have to take them on. We have shown that the institutions shaped by the innovation environment of a country, such as the extent of R&D, the quality of scientific research and the collaboration between companies, universities and governments, play a critical role in shaping those objectives. Countries with a poor innovation environment, mainly located in the European South and East, do substitute robots for labour, but countries with a more favourable environment, such as the United States, Germany and the Nordic countries, might even add labour when they recruit more robots. Regressions with non-manufacturing production sectors (agriculture, mining and utilities) show that robots substitute hours in all countries but less so in countries with good innovation systems; in the biggest user of robots, transport equipment, there is also evidence that there is more substitution than in other sectors, but in electronics and electrical equipment the opposite holds.

We have shown in a simple model of labour-robot substitutions that whether robots replace or complement labour depends on the relation between two elasticities, the elasticity of the demand for the final product and the elasticity of substitution in production. If the elasticity of demand exceeds the elasticity of substitution robots and workers are complementary. We have argued that there are two channels in this framework which might imply that a more favourable innovation environment might be associated with higher robot input and employment. The first is based on arguments that firms with stakeholder and other community objectives, taking into account their employees' interests and views, are more likely to have lower elasticities of substitution between workers and robots; namely, they are more likely to treat workers and robots as complements. We have summarized some evidence that shows that such firms also do more R&D. The second is based on the open economy. Countries that do more innovation gain a comparative advantage in international markets for manufactures and through exports experience a higher elasticity of demand for their final products than firms in countries that supply exclusively their domestic market. The Nordic countries might fit the first argument and Germany and the United States the second. Indirect support for our tradeables argument is also provided by our finding that the innovation environment plays much more limited role in non-manufacturing sectors, which always substitute robots for labour.

Overall, our results point to the fact that it is not possible to use estimates from one country to make inferences about robot-labour substitutions in another, even if the countries are broadly similar. There are interactions between robot-labour substitutions and other features of the economy which influence the estimated elasticities. We have identified one - the innovation environment - but there could be others that future work could identify.

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8 Appendix

8.1 The model: solution and proofs

We derive explicit solutions for the employment allocations from the equations of the model. The consumption allocations satisfy the marginal rate of substitution conditions,

$$\frac{c_1}{c_1^*} = \left(\frac{\psi}{1-\psi}\right)^{\eta}\left(\frac{p_1}{p_1^*}\right)^{-\eta} \tag{17}$$

$$\frac{\tilde{c}_1}{c_2} = \left(\frac{\omega}{1-\omega}\right)^{\varepsilon}\left(\frac{\tilde{p}_1}{p_2}\right)^{-\varepsilon} \tag{18}$$

$$\tilde{p}_1 = \left[\psi^{\eta} p_1^{1-\eta} + (1-\psi)^{\eta} p_2^{*1-\eta}\right]^{1/(1-\eta)} \tag{19}$$

We divide (4) by (6) to obtain,

$$\frac{p_1 A_1}{p_2 A_2}(1-\beta)\left(\frac{z}{H_1}\right)^{1/\sigma} = 1. \tag{20}$$

Dividing also (4) by (5) we obtain the equilibrium solution for robot density,

$$\frac{R}{H_1} = \left(\frac{1-\beta}{\beta}\rho\right)^{-\sigma} \tag{21}$$

From the definition of z in (2), we obtain,

$$\frac{z}{H_1} = \left[1-\beta+\beta\left(\frac{R}{H_1}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \tag{22}$$

and so from (21), after some simplification,

$$\frac{z}{H_1} = (1-\beta)^{-\sigma}\left[(1-\beta)^{\sigma}+\beta^{\sigma}\rho^{-(\sigma-1)}\right]^{\frac{\sigma}{\sigma-1}}. \tag{23}$$

Labour productivity in sector 1 is given by $A_1 z/H_1$ so it is immediately obtained from (23).

To get relative prices we substitute (23) into (20) to get,

$$\frac{p_1}{p_2} = \frac{A_2}{A_1}\left[(1-\beta)^{\sigma}+\beta^{\sigma}\rho^{-(\sigma-1)}\right]^{-\frac{1}{\sigma-1}}. \tag{24}$$

We note that the derivations so far have not used any of the trade variables so they hold for the closed and open economy, independently of trade magnitudes. The results of Proposition 1 follow immediately from these derivations. Robot density is increased by a fall in ρ from (21), productivity in sector 1 is increased because of (23) and relative prices fall because of (24).

Consider now the closed economy model, by setting $\psi = 1$ in the utility function (9) and $c_1^{**} \equiv 0$. By market clearing $c_1 = A_1 z$ and $c_2 = A_2 H_2$ and from (18),

$$\frac{A_1 z}{A_2 H_2} = \left(\frac{\omega}{1-\omega}\right)^{\varepsilon}\left(\frac{p_1}{p_2}\right)^{-\varepsilon}. \tag{25}$$

Therefore,

$$\begin{aligned}\frac{H_1}{H_2} &= \left(\frac{A_1 z}{A_2 H_1}\right)^{-1}\left(\frac{\omega}{1-\omega}\right)^{\varepsilon}\left(\frac{p_1}{p_2}\right)^{-\varepsilon}\\ &= \left(\frac{A_1}{A_2}\right)^{\varepsilon-1}\left(\frac{\omega}{1-\omega}\right)^{\varepsilon}(1-\beta)^{\sigma}\left[(1-\beta)^{\sigma}+\beta^{\sigma}\rho^{-(\sigma-1)}\right]^{\frac{\varepsilon-\sigma}{\sigma-1}}. \quad (26)\end{aligned}$$

From this and the resource constraint $H_1 + H_2 = 1$, we obtain the closed-economy result of Proposition 2.

With imports and exports output markets clear according to (12) and (13), so (25) changes to,

$$\frac{A_1 z}{A_2 H_1}\frac{H_1}{H_2} = \frac{c_1 + c_1^{**}}{c_2} \tag{27}$$
$$= \frac{c_1}{c_2}\frac{y_1}{c_1}. \tag{28}$$

making use of the MRS conditions we get,

$$\frac{c_1}{c_2} = \left(\frac{\tilde{c}_1}{c_1}\right)^{-1}\left(\frac{\tilde{c}_1}{c_2}\right) \tag{29}$$
$$= \left(\frac{\tilde{c}_1}{c_1}\right)^{-1}\left(\frac{\omega}{1-\omega}\right)^{\varepsilon}\left(\frac{\tilde{p}_1}{p_2}\right)^{-\varepsilon} \tag{30}$$
$$= \left(\frac{\omega}{1-\omega}\right)^{\varepsilon}\left(\frac{p_1}{p_2}\right)^{-\varepsilon}\left(\frac{\tilde{p}_1}{p_1}\right)^{-\varepsilon}\left(\frac{\tilde{c}_1}{c_1}\right)^{-1}. \tag{31}$$

Comparing now (28)-(31) with (25), we find that the solution for H_1/H_2 in the open economy has the same terms on the right-hand side as in (26) except for one multiplicative term, which we denote by $F(.)$,

$$F(.) = \frac{y_1}{c_1}\left(\frac{\tilde{p}_1}{p_1}\right)^{-\varepsilon}\left(\frac{\tilde{c}_1}{c_1}\right)^{-1}. \tag{32}$$

This is the only term that contains foreign trade variables, as one of the first two terms is a ratio of preference parameters and the other is solved in (24) in terms of domestic parameters only. As might be expected, if $\psi = 1$ and $c^{**} = 0$, $F(.) = 1$, giving the closed-economy solution.

Returning now to (32), we can express $(\tilde{p}_1/p_1)^{-\varepsilon}(\tilde{c}_1/c_1)^{-1}$ in terms of model parameters and the "terms of trade" p_1/p_1^* :

$$\left(\frac{\tilde{p}_1}{p_1}\right)^{-\varepsilon}\left(\frac{\tilde{c}_1}{c_1}\right)^{-1} = \left[\psi + (1-\psi)\left(\frac{c_1^*}{c_1}\right)^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{1-\eta}} \tag{33}$$
$$= \left(\frac{\tilde{p}_1}{p_1}\right)^{-\varepsilon}\left[\psi + (1-\psi)\left(\frac{1-\psi}{\psi}\right)^{\eta-1}\left(\frac{p_1^*}{p_1}\right)^{1-\eta}\right]^{\frac{\eta}{1-\eta}} \tag{34}$$
$$= \psi^{\eta}\left(\frac{\tilde{p}_1}{p_1}\right)^{\eta-\varepsilon}. \tag{35}$$

The first term of (32), y_1/c_1, depends on the volume of exports, which is unknown. Moreover, without an equation for trade balance, the equilibrium terms of trade are also unknown. Equation (35) at least shows that for given exports (more precisely for given proportionality relation between exports and domestic consumption of home-produced manufacturing goods) a fall in p_1/p_1^* has positive impact on employment in sector 1 for as long as $\eta > \varepsilon$. By differentiation, $F'(p_1/p_1^*) < 0$ if and only if $\eta > \varepsilon$, for a given y_1/c_1. A rise in exports everything else constant trivially produces another positive influence on H_1, so under the reasonable assumption that exports are a falling function of p_1/p_1^*, we obtain that a fall in p_1/p_1^* reinforces the positive impact of the import substitution effect on domestic manufacturing employment.

8.2 Data: Definitions and sources

Hours of work – The total number of annual hours worked by all persons engaged in production by industrial group, 2006-2016. Source: EU KLEMS, 2019 release.

Robots – The total number of robots by industrial group, annual observations for 2006-2016, as estimated by the International Federation of Robotics. The IFR estimates the operational stock by assuming a service life of 12 years followed by an immediate withdrawal from service. Source, IFR (2017)

Robot density – The number of robots divided by hours of work in millions. In the early years, a very small number of year-country-industry entries show zero robots or an unexplained big jump, which we treat as omitted variables.

Capital – We use the EU KLEMS 2019 dataset, listed by industry, country and year, which provides information on net capital stock, volume 2010 reference prices. We convert to US dollars using PPP exchange rates from the OECD, https://data.oecd.org/conversion/purchasing-power-parities-ppp.htm . Total capital includes ten asset types: residential structures; total non-residential investment; transport equipment; computing equipment; communications equipment; other machinery, equipment and weapons systems; cultivated assets and intellectual property products including R&D, computer software and databases, and others. EU KLEMS calculates the stock using the perpetual inventory method. We exclude R&D from our measure of the capital stock.

ICT –EU KLEMS defines ICT capital as computing equipment, communications equipment and computer software and databases. We take this from the definition of overall capital and use its ratio to total capital in our regressions.

Compensation of employees – Compensation includes wages, salaries and all the other costs of employing labour which are borne by the employer.

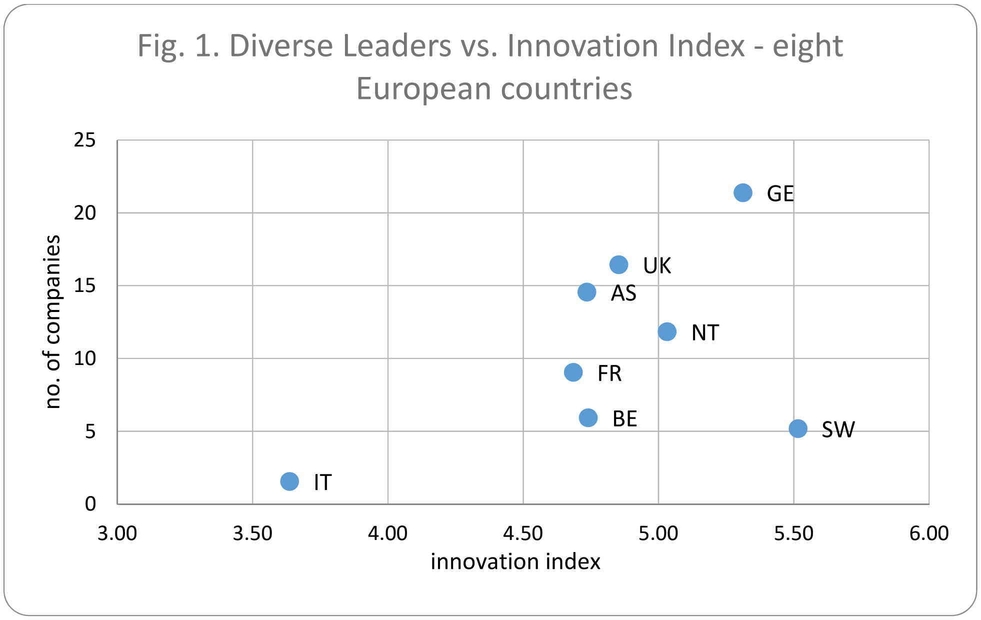
We convert to constant 2010 US dollar prices using PPP exchange rates. For hourly compensation we divide the total compensation in EU KLEMS 2019 by hours of work, in millions.

Innovation Index – The average of the first six indicators of Pillar 12 of the World Economic Forum *Global Competitiveness Index*, available on a consistent basis for all countries in our sample in 2006-2016. Two additional composite indicators that we used are the *Global Innovation Index* and the European Union *Summary Innovation Index*. The *Global Innovation Index* (GII) was first published in 2007 by Cornell University, INSEAD and the World Intellectual Property Organization. The *Summary Innovation Index* (SII), developed by the European Commission, covers European countries only.

Instrumental variables – The following instruments were used. Robot density in South Korea, defined as in our countries. The total number of annual hours worked by industrial groups is available up to 2012. We impute the industry-level hours worked for the years 2013-2016 using the average annual change of an industry's hours worked during the years 2004-2012. Sources: IFR (2017), World KLEMS, http://www.asiaklems.net/.

Robot density in Germany, annual observations for 1993-2006. Sources: EU KLEMS, 2012 release; 2019 release, IFR (2017).

The number of patents applications in South Korea, by industrial group, from 1980 to 1994. The number of patents is divided by population, in millions. Sources: European Patent Office, the Autumn 2018 edition, population from the World Bank database.



Notes: The vertical axis shows the number of companies from each of eight countries in the *Financial Times* diveristy leaders rank, top 100. The actual count is divided by the total number of enterprises in the country, adjusted to have sample mean 1.

Table 1. Country means of key variables

Country	Innovation Index scale 1-7	Annual Hours (millions)	Robot density	
			manufacturing	Non-manuf.
Greece	3.40	867	0.26	0.63
Italy	3.79	8,713	10.91	0.04
Spain	3.92	5,421	9.21	0.1
Czechia	4.24	2,003	2.31	0.04
Austria	4.73	1,341	5.98	0.27
France	4.81	5,820	11.06	0.24
Belgium	4.96	886	7.56	0.09
Netherlands	4.98	1,231	4.57	0.21
Denmark	4.99	469	12.16	1.52
UK	5.04	5,461	3.49	0.1
Germany	5.28	10,115	14.3	0.04
Sweden	5.36	1,045	8.57	0.45
Finland	5.49	745	8.76	0.12
USA	5.50	24,403	5.44	0.02

Notes

For the construction of the innovation index see text.

Annual hours are defined as the annual average of total hours actually worked in the sectors in the sample, 2006-2016.

Robot density is the unweighted average of the annual ratio of robots in production to hours of work, again for the sectors in the sample.

In the calculation of sample means only observations for which a positive number of robots is shown are included.

Table 2. Industry means of key variables

Industry	Annual hours (millions)	Robot density
Electronics	455	3.90
Food and beverages	663	3.32
Metal	722	8.24
Plastics and chemical	745	6.13
Textiles	201	1.16
Transport Equipment	487	27.89
Wood and paper	331	1.66
Agriculture	989	0.09
Utilities	272	0.04
Mining and quarrying	63	0.60

Notes

Annual hours is defined as the annual average of hours of work in each sector and country for which the reported number of robots is positive.

Robot density is the unweighted average of the annual ratio of robots in production to hours of work (in millions) for all countries in the sample.

In the calculation of sample means only observations for which a positive number of robots is shown are included.

Table 3. Results for manufacturing industries

	Dependent variable in all regressions: log hours by country, industry and year, $\ln(H_{ict})$			
	(1)	(2)	(3)	(4)
	OLS	OLS	IV	IV
Independent variables				
$\ln(R_{ict}/H_{ict})$	-0.015	-0.339	-0.001	-0.538
	(0.006)	(0.037)	(0.008)	(0.049)
$\ln(R_{ict}/H_{ict})\ *V_{ct}$		0.069		0.115
		(0.008)		(0.010)
$\ln(K_{ict})$	0.723	0.700	0.716	0.676
	(0.011)	(0.011)	(0.011)	(0.012)
$\ln(ICT_{ict}/K_{ict})$	0.097	0.063	0.094	0.037
	(0.014)	(0.014)	(0.014)	(0.014)
$\ln(W_{ict}/H_{ict})$	-0.299	-0.245	-0.329	-0.247
	(0.035)	(0.035)	(0.037)	(0.037)
country dummies	yes	yes	yes	yes
time dummies	yes	yes	yes	yes
industry dummies	no	no	no	no
Number of obs.	1,044	1,044	1,044	1,044
F(27, 1016)	1,164		1,157	
F(28, 1015)		1,207		1,158
Cragg-Donald Wald F statistic			1,192	482

Notes

Robust standard errors in parentheses.

The instrument used is robot density in South Korea over the period of the sample.

Table 4. Net elasticity estimates by country (OLS)

country	net estimate	ΔH per robot	country	net estimate	ΔH per robot
Greece	-0.105 (0.012)	-241,742	Netherlands	0.004 (0.006)	550
Italy	-0.078 (0.009)	-8,197	Denmark	0.004 (0.006)	288
Spain	-0.069 (0.008)	-7,876	United Kingdom	0.008 (0.006)	1,984
Czechia	-0.047 (0.007)	-10,541	Germany	0.024 (0.007)	1,341
Austria	-0.013 (0.006)	-1,736	Sweden	0.030 (0.008)	2,395
France	-0.008 (0.006)	-900	Finland	0.039 (0.008)	4,302
Belgium	-0.002 (0.006)	-224	United States	0.039 (0.009)	4,679

Notes

The column headed net estimate shows the net elasticity of hours on robot density obtained from Table 3, with robust standard errors for the net estimate in parentheses

The column headed ΔH per robot shows the change in the number of annual hours for each additional robot, evaluated at the mean values of the last five years (2012-16) for all countries except for Greece, which is evaluated at the average of the last three years of the sample, because of missing observations.

Table 5. Manufacturing industries breakdowns

Independent variables	OLS regression, Dependent variable $\ln(H_{ict})$
$\ln(R_{ict}/H_{ict}) * I_{\nu\tau}$	-0.453
	(0.041)
$\ln(R_{ict}/H_{ict}) * I_{\varepsilon}$	-0.413
	(0.117)
$\ln(R_{ict}/H_{ict}) * I_{\alpha}$	-0.149
	(0.053)
$\ln(R_{ict}/H_{ict}) * I_{\nu\tau} * V_{ct}$	0.098
	(0.009)
$\ln(R_{ict}/H_{ict}) * I_{\varepsilon} * V_{ct}$	0.105
	(0.024)
$\ln(R_{ict}/H_{ict}) * I_{\alpha} * V_{ct}$	0.026
	(0.011)
$\ln(K_{ict})$	0.678
	(0.012)
$\ln(ICT_{ict}/ K_{ict})$	0.025
	(0.015)
$\ln(W_{ict}/H_{ict})$	-0.253
	(0.036)
country dummies	yes
time dummies	yes
industry dummies	no
Number of obs.	1,044
F(32, 1011)	1,150

Notes

Subscript $\nu\tau$ denotes low-tech industries, ε electronics and α transport equipment.

Robust standard errors in parentheses.

Table 6. Manufacturing and non-manufacturing industries

Independent variables	OLS regression Dependent variable $\ln(H_{ict})$
$\ln(R_{ict}/H_{ict})$ *I_ρ	-0.159
	(0.037)
$\ln(R_{ict}/H_{ict})$ *I_μ	-0.239
	(0.037)
$\ln(R_{ict}/H_{ict})$ *I_ρ*V_{ct}	0.019
	(0.008)
$\ln(R_{ict}/H_{ict})$ *I_μ*V_{ct}	0.053
	(0.008)
$\ln(K_{ict})$	0.663
	(0.010)
$\ln(ICT_{ict} / K_{ict})$	0.057
	(0.012)
$\ln(W_{ict}/H_{ict})$	-0.243
	(0.026)
country dummies	Yes
time dummies	Yes
industry dummies	for 3 non-manufacturing sectors
Number of obs.	1364
F(33, 1330)	1237

Notes

Subscript μ denotes the manufacturing sectors in our sample and ρ the three non-manufacturing sectors (agriculture, mining and quarrying and utilities).

Robust standard errors in parentheses.

Table 7. Components of the innovation index

	Dependent variable in all regressions ln(H_{ict})					
	Innovation capacity	Scientific research quality	R&D company spending	University industry collaboration	Government Tech procurement	Scientist Engineer available
$\ln(R_{ict}/H_{ict})$	-0.275	-0.277	-0.240	-0.266	-0.204	-0.030
	(0.032)	(0.032)	(0.027)	(0.027)	(0.031)	(0.046)
$\ln(R_{ict}/H_{ict})$	0.054	0.050	0.050	0.053	0.049	0.003
$*V_{ct}$	(0.007)	(0.006)	(0.006)	(0.005)	(0.009)	(0.013)
Zero net effect	5.13	5.51	4.84	4.99	4.19	10.5
No. obs.	1044	1044	1044	1044	1044	1044

Notes

The coefficients in this table were estimated with regressions like the one in column (2) of Table 3, with each of the six components of the National Innovation Index replacing the aggregate index in turn.

Robust standard errors in parentheses.