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## ABSTRACT

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# Productive Robots and Industrial Employment: The Role of National Innovation Systems\*

In a model with robots, and automatable and complementary human tasks, we examine robot-labour substitutions and show how they are influenced by a country's "innovation system". Substitution depends on demand and production elasticities, and other factors influenced by the innovation system. Making use of World Economic Forum data we estimate the relationship for thirteen countries and find that countries with poor innovation capabilities substitute robots for workers much more than countries with richer innovation capabilities, which generally complement them. In transport equipment and non-manufacturing robots and workers are stronger substitutes than in other manufacturing.

**JEL Classification:** J23, L60, O33, O52

**Keywords:** robots-employment substitution, automatable tasks, complementary task creation, innovation environment, industrial allocations

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# 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 examine the impact of the introduction of robots on the equilibrium allocation of hours of work, in an economy with automatable and non-automatable tasks; namely, on hours spent on tasks with high and low robot substitution elasticities. In a theory section we develop a conventional model based on a production function with two different labour inputs, one a substitute and the other a complement to robots. We show that allocations depend on several elasticities of demand and production, and a fall in the price of robots could lead to either an increase or a decrease in overall hours of work, depending on the values taken by these elasticities. We then switch to multi-country empirical work and show that the institutional structures of a country that are summarized in the country's "national innovation system" play a crucial role in determining which effects will dominate the equilibrium responses of hours to the introduction of more robots in production.

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.<sup>1</sup> A national innovation system depends crucially on the quality of human capital that firms have access to, but as we make explicit in the main part of the paper, an effective national innovation system requires more than just good quality human capital. There are complementarities between human capital and other institutional features that make up a strong innovation system.

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. In our empirical 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 thirteen

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<sup>1</sup>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 Co-operation and Development (OECD, 1997 and 1999).

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 not precisely estimated, 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 when robots are introduced.

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.<sup>2</sup> An innovation of our CES production structure in manufacturing is that hours are employed in two types of tasks. One type has high elasticity of substitution with robots, which we call automatable and intuitively associate with production workers, and a second one has low elasticity of substitution, which we associate with tasks such as management, research, sales and robot maintenance. Intuitively we can think of the automatable part as producing intermediate goods which are then combined with the second type of task into final output. The economy is closed by a second sector that has a simple linear technology in labour only.

In the derivation of the impact of a lower robot price on hours, we find that several elasticities interact to produce the equilibrium net effect. These are the elasticity of substitution between hours and robots in the automatable part of production, which works against hours when robots are introduced; the complementary elasticity in the non-automatable part, which works to increase hours when the intermediate output of the automatable part increases; and the elasticity of final demand for output, which is influenced by the substitution possibilities of both domestic demand and demand for exports and imports, given that manufacturing produces tradable output.

The main result of our theoretical model is that if the demand elasticity for final output exceeds the low elasticity of substitution between the intermediate output and the labour employed in non-automatable tasks, there are two opposing influences on overall hours in manufacturing: a negative one that originates in the production technology of the automatable part and a positive one that originates in the comparison between the final demand elasticity and the supply elasticity in the production of final output. The innovation in this result is that unlike earlier derivations, the second

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<sup>2</sup>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 model.

effect does not depend on a comparison of the high elasticity of substitution between robots and hours in the automatable part of production, but on the low elasticity in the non-automatable part.<sup>3</sup> Of course, the final outcome might still be negative, in the case where the negative effect that originates in the automatable part dominates the positive one. This is where we bring in the national innovation system and argue that it influences the relative strengths of each effect, such that in more innovative countries the positive (complementary) effect is stronger than the negative (substitutable) effect.

There are two channels in which the innovation environment of a country can have this effect on robot-labour substitutions. The first influences the elasticity of demand for manufacturing output. Although in a closed economy the elasticity for aggregate manufacturing output is small (closer to zero than one), it is higher for individual sectors and especially for sectors that trade. For reasons explained later in this paper, a country with a better innovation system will have higher manufacturing productivity, the sector that benefits most from innovation. As Kiminory Matsuyama (2009) has shown, a country with relatively faster productivity growth shifts the comparative advantage in the production of manufactured goods in its favour. This raises its elasticity for final output and has a positive impact on employment, which mitigates the negative closed-economy effect.

The second channel through which the innovation environment influences the robot-labour substitution is related to the availability of good quality human capital. Our model is one of homogeneous labour so we cannot formalize this idea explicitly but we can still represent it within the parameters of our model, by reasoning as follows. The complementary tasks of production, especially those in research, management, design, marketing and new technology implementation, require highly qualified labour. In countries that have better availability of scientists and engineers, and more generally better quality human capital, firms will create more complementary tasks to employ more of these workers, if it increases their profit. We show that if it is profitable for the firm to operate on average with more complementary tasks, then a lower robot price shifts relatively more weight to a positive impact on

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<sup>3</sup>There is a large literature that derives results of the kind referred to here, associated with the structural transformation of economies that experience uneven technological progress. Our model can be interpreted as one in which technological progress takes place only in the sector producing robots, which are then used as inputs in some other sectors. See for example Berthold Herrendorf, Richard Rogerson and Akos Valentinyi (2014) for a survey. For the “earlier derivations” referred to in the text see Graetz and Michaels (2018) and an earlier version of this paper that circulated in September 2020 as Discussion Paper no. CFM-DP2020-23 of the Centre for Macroeconomics of the London School of Economics.

overall hours than to a negative one.<sup>4</sup>

We then turn to data and test our propositions about the role of the national innovation system in robot-hours substitutions. Our data are annual observations for 2006-2016 from thirteen OECD countries.<sup>5</sup> 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). They examined the impact of robots on productivity 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 they found that robots do not influence it, except for a small impact on low-skill workers. We use annual observations, which give richer results for hours of work, and show that taking into account the national innovation system ties down a statistically strong impact of robots on employment that varies across countries and sectors.

Making use of a similar data set, Francesco Carbonero, Ekkehart Ernst and Enzo Weber (2018) find a small negative impact on hours in 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.<sup>6</sup>

We take country-industry data from the International Federation of Robotics (IFR) and EU KLEMS to compute the number of robots per million working hours and some other economic variables. To compute our innovation index we extract from the World Economic Forum’s *Global Competitiveness Report* (Klaus Schwab, 2017, and earlier versions) country-level measures of “innovation capacity.” Our index of a country’s national innovation system is the simple average of six scores for as many indicators: the avail-

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<sup>4</sup>Note that this is not a trivial prediction driven by the assumptions. On average a firm could operate with more complementary tasks and yet shift production to the automatable part at a lower robot price, because of the lower cost of production that it implies.

<sup>5</sup>The thirteen countries are the United States and twelve European countries, Austria, Belgium, Chechia, Denmark, France, Finland, Germany, Italy, Netherlands, Spain, Sweden, and the United Kingdom.

<sup>6</sup>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 Pascual Restrepo (2020) for a study of the impact of robots in US commuting zones and Francesco Chiacchio, Georgios Petropoulos and David Pichler (2018) for local labour markets in the European Union. Both sets of authors find large negative effects on local employment.

ability 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.

In our tests we found that there are statistically significant differences between the two “high-tech” sectors of electronics and electrical goods and transport equipment, and the “low-tech” sectors that make up the rest of our sample. The innovation system plays an important role in signing the impact of robot density on hours in all manufacturing sectors, but not in non-manufacturing. Its biggest impact is in electronics, which is not surprising given the innovation activity in that sector. The introduction of robots in that sector has a strong negative impact on hours in countries with a poor innovation system, like Italy and Spain, but a strong positive impact in countries with a strong innovation system, like Germany and the United States. In transport equipment, which is by far the biggest user of robots, all statistically significant coefficients are negative but the national innovation system still plays an important role; in countries with a strong system the estimates are not significantly different from zero. We also tested substitutions in three production sectors that do not belong to manufacturing, which are very small users of robots, and found that robots substitute hours regardless of the innovation system of the country.

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.

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 two 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 formulate an equilibrium model that can be used to derive the connections between robots and hours of work. In section 3 we discuss how the results of the model are affected by a country's national innovation system. The description in this section gives the bare-bones of a model and derives the main results for the closed economy.

The empirical literature that calculates the number of jobs that robots could potentially replace usually lists tasks and examines whether robots have the capability of performing these 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 particular tasks.<sup>7</sup> Here we follow a more conventional production function approach that is consistent with two observations. First, a company that employs workers in tasks that can be done by robots also employs workers in tasks that are complementary to robots. When new robots are introduced, the company reallocates its labour input across those tasks. If this reallocation involves increasing the number of hours allocated to tasks that are complementary to robots, statistically it will show up as new tasks (or jobs) created (Lin, 2011, Acemoglu and Restrepo, 2019). Second, as in the structural transformation literature, the introduction of robots is not uniform across sectors, and this causes employment reallocations across sectors (for references see footnote 9).

To illustrate our first point, which is the new feature in our production technology, consider a car manufacturer. There is a car production side, which is capital intensive and employs robots and workers, who are engaged in tasks that can be automated. There is also a research and administrative side, which consists of managers, research workers, new model developers, sales people, drivers who test and demonstrate cars, capital maintenance workers, real estate maintenance workers, and possibly others. This side of the overall production is labour-intensive and complementary to the output of the production side. The elasticity of substitution between workers and cars on this part of production is low, as the people working here are engaged in improving car quality, improving the organization of production, and when

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<sup>7</sup>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 Pascual Restrepo (2020) and Georg Graetz and Guy Michaels (2018). A notable early exception using more conventional techniques to study the substitutions between labour and capital is Joseph Zeira (1998).

the output is done, turn the cars into company revenue.<sup>8</sup>

Companies that introduce robots are competing with other companies that provide services in which humans have the comparative advantage. This competition has price and wage implications that feed back on the impact of robots on employment in the robot-using sectors of the economy. Because of this feedback from prices, we need an equilibrium model to evaluate the net impact of robots on employment.

Given that robots are introduced in their very large majority in manufacturing, our argument is essentially that as robots displace workers in manufacturing, new tasks are created in manufacturing itself to take on some of the workers losing their jobs, but other tasks and jobs are created in the service sectors of the economy to take any workers leaving manufacturing. Our argument will be that manufacturing companies in countries with a stronger innovation environment are more likely to create new tasks for displaced workers, than do companies in countries with weaker innovation systems. The reasons for this are discussed more fully in the next section.

We consider a full employment model in which price and wage adjustments ensure that there are enough jobs created to employ all displaced workers. In the empirical work we estimate the impact of robots on hours of work in the manufacturing sector, which introduces the robots. Our model and estimation are partial, in the sense that we ignore other long-term trends that have been reducing manufacturing employment in all countries in our sample. These trends are the topic of the structural transformation literature.<sup>9</sup>

Our model has two sectors. Sector 1 produces a consumption good, which is tradeable if the economy is open, and has a technology that can use both labour and robots. Sector 2 uses only labour as an input and produces a consumption good that is not tradeable. Sector 2 is modelled as a labour intensive sector with linear technology. We model a closed economy but discuss in the next section the implications of foreign trade for employment, which turn out to be important for our empirical work with several small open economies. Sector 1 can be identified with manufacturing, and 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

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<sup>8</sup>Although our model is one of homogeneous labour, in the data we would expect the workers that are close substitutes to robots to be the less skilled workers employed by the company, and those in the complementary tasks, especially the managerial and research workers, to be the more skilled. See section 3 for more discussion of this issue.

<sup>9</sup>See for example L. Rachel Ngai and Christopher Pissarides (2007), Daron Acemoglu and Veronica Guerrieri (2008) and Berthold Herrendorf, Richard Rogerson and Akos Valentinyi (2014)

at a fixed and exogenous price  $\rho$ , expressed in wage units. This price has been falling in the international economy because of technological improvements in the production of robots and it is the driving force of changes in our model.<sup>10</sup>

As discussed above, our innovation in the theoretical part of this paper is that a typical robot-using sector has a two-part production structure. One part consists of tasks that can be performed by both robots and labour, with some finite but large elasticity of substitution, and produces an intermediate output  $F$ . We call this the automatable part of production. A second part of the overall production structure employs labour in non-automatable tasks, which is combined with the intermediate goods produced by the automatable part to produce the final output of the sector. We call this side of production the non-automatable part.

The automatable part has production function,

$$F = \left[ \alpha H_{1R}^{(s-1)/s} + (1 - \alpha) R^{(s-1)/s} \right]^{s/(s-1)}, \quad (1)$$

where  $H_{1R}$  are the hours supplied by human labour,  $R$  are the robots employed in the sector, and  $\alpha \in [0, 1]$ ,  $s > 0$  are parameters. Introducing other productivity parameters, which might be neutral or factor-augmenting, would make no difference to our results. By our assumption that tasks in this sector are automatable, we derive our qualitative results under the restriction  $s > 1$ .

Parallel to this production activity, firms in the robot-using sector employ labour in the non-automatable part of production, which is influenced by the introduction of robots through the intermediate output  $F$ . We show this by writing the aggregate production function of the sector as follows:

$$Y_1 = A_1 \left[ \beta H_{1N}^{(\sigma-1)/\sigma} + (1 - \beta) F^{(\sigma-1)/\sigma} \right]^{\sigma/(\sigma-1)}. \quad (2)$$

Here  $Y_1$  is the output of sector 1,  $H_{1N}$  are the hours of work employed in the non-automatable part of production, and  $\sigma > 0$  is the elasticity of substitution between the automatable sector of production and the non-automatable one. The parameter  $\beta \in [0, 1]$  shows the intensity of non-automatable labour in the overall production process of the industrial sector.

In conformity with our discussion, we assume that  $\sigma < 1$ ; i.e., that the output of the automatable part of production is complementary to the labour employed in the non-automatable part. As in our previous example, a manufacturing company needs R&D, design, administrative and advertising services, supplied by labour, to promote its output. The manufacturing firm

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<sup>10</sup>See International Federation of Robotics (2017) and Georg Graetz and Guy Michaels (2018).

chooses its inputs,  $R$ ,  $H_{1R}$  and  $H_{1N}$  subject to given prices of output  $p_1$  and prices of factors, respectively  $\rho W$ ,  $W$  and  $W$ , to maximize profits.

We complete the description of the labour market by introducing the labour intensive sector 2,

$$Y_2 = A_2 H_2, \quad (3)$$

with obvious notation that parallels sector 1, and output price  $p_2$ .

The demand side of the model is derived from the consumer maximization problem,

$$\max_{c_1, c_2} U(c) = \ln \left[ \omega c_1^{(\varepsilon-1)/\varepsilon} + (1-\omega) c_2^{(\varepsilon-1)/\varepsilon} \right]^{\varepsilon/(\varepsilon-1)} \quad (4)$$

$$p_1 c_1 + p_2 c_2 \leq Y, \quad (5)$$

where  $c_1$  and  $c_2$  are the consumption levels of goods 1 and 2 and  $Y$  is aggregate income. The parameters  $\omega$  and  $\varepsilon$  satisfy  $\omega \in (0, 1)$  and  $\varepsilon \geq 0$ .

Labour markets clear subject to the resource constraint,

$$H_1 + H_2 \leq 1, \text{ where} \quad (6)$$

$$H_1 = H_{1R} + H_{1N}. \quad (7)$$

Output markets clear according to

$$c_1 \leq Y_1, \quad c_2 \leq Y_2 \quad (8)$$

$$Y = p_1 Y_1 + p_2 Y_2 \quad (9)$$

**Definition.** *Equilibrium is defined by an allocation for consumption goods that satisfies the consumer maximization problem (4)-(5), a labour and robot allocation that maximizes profit  $p_1 Y_1 - (H_{1R} + H_{1N})W - R\rho W$ , subject to exogenous relative price  $\rho$  and the resource constraint (6), and prices  $p_1, p_2$  and  $W$  that satisfy the market clearing conditions (8)-(9).*

We state here the main results of the model in the form of two Propositions and collect all derivations and proofs in Appendix 1.

**Proposition 1** *Lower robot price raises robot density ( $R/H_1$ ) and output per hour ( $Y_1/H_1$ ) in sector 1 and lowers relative price ( $p_1/p_2$ ).*

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 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 as an input. The results of Proposition 1 about output per hour have been the focus of the empirical work of Graetz and Michaels (2018) and we will not test them further.

**Proposition 2** *For  $\beta \in (0, 1)$ , lower robot price has two effects on hours of work in sector 1. A negative one that holds whenever  $\sigma < s$  (which we always assume) and a second one which is also negative if  $\varepsilon < \sigma$ , zero if  $\varepsilon = \sigma$  and positive if  $\varepsilon > \sigma$ . For  $\beta = 0$ , lower robot price lowers hours whenever  $\varepsilon < s$ .*

The case  $\beta = 0$  is the standard CES production function formulation of capital-labour substitutions in the face of sectoral productivity growth (refer, e.g., to the structural transformation literature). A fall in the price of robots is a technological improvement that raises sector 1 output, reduces its relative price and increases its relative demand with elasticity  $\varepsilon$ . If the elasticity of demand is low ( $\varepsilon < s$ ) the rise in demand is not enough to absorb the additional output, so hours have to fall to restore equilibrium. We argue in the next section, summarizing results from the empirical literature, that the restriction  $\varepsilon \leq s$  is likely to be satisfied by the data.

Once the second type of labour input is allowed, the result changes dramatically. Whereas the high  $s$  still has a negative impact on hours, if  $\varepsilon$  exceeds  $\sigma$ , which is low by the nature of the tasks that this type of labour performs, there is also a positive impact on hours, which might dominate the negative impact. Under the plausible restriction (see the next section)  $s > \varepsilon > \sigma$ , the net impact of lower robot price on hours of work is ambiguous. The intuition for this ambiguous result, which emerges from the expressions derived in Appendix 1, is the following.

Referring to the production function for final output (2), we see that output can be thought of as produced by a two-factor CES with elasticity of substitution  $\sigma$ . In that case the standard result emerges, that if the elasticity of demand exceeds the elasticity of substitution, technological progress increases employment. But in addition to the demand for final output, there is a second production function for the intermediate output  $F$ , for which the demand is from the final output producer with elasticity  $\sigma$ , whereas the production elasticity is  $s$ . Therefore, in parallel with the standard result, technological progress reduces employment in this production function if the elasticities satisfy  $\sigma < s$ . In our formulation, the positive impact from  $\varepsilon \geq \sigma$  applies to both labour inputs,  $H_{1N}$  and  $H_{1R}$ , because they are both in (2), whereas the negative impact affects only  $H_{1R}$ , which is the only one used in the production of the intermediary good.

### 3 The innovation environment

Our model points to three elasticities of critical importance in signing the net impact of robot price on hours of work,  $s$ ,  $\varepsilon$  and  $\sigma$ .<sup>11</sup> The elasticities  $s$  and  $\sigma$  are technological constants of the production function. But in the open economy, the relevant demand elasticity for manufacturing goods is not constant, even if the elasticity of substitution between consumption goods in the utility function is a constant. It is a weighted average of the elasticities of substitution between foreign and domestic goods and domestic manufacturing and non-manufacturing goods. Making use of this property, which is demonstrated formally in this section, we argue that the a better innovation environment mitigates the negative impact of robots on hours through two channels. First, through the elasticity of demand for manufacturing goods and second through the relative weights that are attached to the two opposing impacts of the fall in robot price on hours when  $\varepsilon > \sigma$ .

Before putting forward the arguments and summarize evidence, we do two things. We first define more precisely our concept of innovation environment and describe the data that we used to construct our innovation index. Second, we make explicit the condition under which the positive impact of a robot price fall dominates the negative one.

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, p. 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. Our index is the average of these six indicators.<sup>12</sup> The country sample means for the index and some

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<sup>11</sup>Richard Baldwin et al. (2021), in a paper that circulated after these sections were completed, also discuss the role of elasticities in signing the direction of capital-labour substitutions. Their model has the first two elasticities of this section but not  $\sigma$  or the innovation environment, which play a critical role here.

<sup>12</sup>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

comments about the data are postponed to section 4.

It is important to realise at this stage that since we measure the innovation environment by “innovation capabilities,” human capital plays an important role in our analysis. Innovation is the result of R&D and R&D is conducted by highly trained employees, working in the non-automatable part of production. Other available innovation indices, discussed in section 6.3, refer more explicitly to the importance of human capital in their construction. It is not surprising therefore that there is a good correlation between our innovation index and the human capital of a country. But a good innovation environment requires more than human capital. It also requires favourable policy, certain types of human capital more than others and generally incentives to companies to spend resources on R&D. This is reflected in the six pillars that make up our innovation index and it is also the reason that we refer to it as the overall innovation index rather than just an index of the quality of human capital.

To derive now the condition under which the positive impact of a robot price fall dominates the negative, we differentiate with respect to robot price expression (37) of the Appendix, which gives the equilibrium ratio  $H_1/H_2$  derived from our model. We derive that the net elasticity is positive when,

$$(\varepsilon - \sigma) \frac{q^{(\sigma-1)/s}}{(1 - \beta)^\sigma \alpha^{\sigma-1} q^{(\sigma-1)/s} + \beta^\sigma} > (s - \sigma) \alpha q^{(\sigma-s)/s}, \quad (10)$$

where  $q$  is defined in the Appendix as a function of parameters, including robot price  $\rho$ , and satisfying  $q'(\rho) < 0$ . The left term is the impact of the price fall on the complementary tasks in the non-automatable part of production, which is positive when  $\varepsilon > \sigma$ , and the right term is the impact of the price fall on hours in the automatable part of production, which is negative because  $s > \sigma$ .

We argue that the innovation environment of a country influences this expression in two ways. First, more innovative countries have a comparative advantage in international markets and trade more in manufacturing goods. We discuss the ways in which trade influences the two sides of (10). Second, in more innovative countries firms employ more workers in complementary tasks. In our model this is shown as a higher  $\beta$  in the production function

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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 did not include it in our index. 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.

of firms in countries with a more favourable innovation environment. We discuss evidence that this is the case and derive the impact of higher  $\beta$  on (10). Before we develop these two arguments, we note that the right-hand side of (10) is a function of technological parameters that cannot be influenced by either international trade or  $\beta$ , the parameter for the creation of complementary tasks. Therefore everything we do in the remainder of this section concerns the impact of the innovation environment on the expression on the left-hand side of (10).

### 3.1 The open economy and the elasticity of demand

In our derivation of a closed economy equilibrium, the elasticity of demand  $\varepsilon$  was derived from a utility function with two goods. In the closed economy and for the whole of manufacturing, this elasticity is likely to be a very small number. In the survey of estimates examined by Ngai and Pissarides (2008), a plausible range for  $\varepsilon$  was found to be between 0 to 0.3. Similar results were derived by Berthold Herrendorf et al. (2013) for value added consumption bundles. These estimates are derived from consumer demand equations or spending shares, mainly from the United States, so they approximate the closed economy values.

Results, however, could be different if we consider individual industries or open economies. Worldwide, the closed economy result holds and robots, like other productivity-enhancing technologies, reduce global manufacturing employment. Individual manufacturing sectors might have a different experience, because of substitution possibilities across products which are either used as final consumption products or as intermediate goods. For example, metal products can be substitutes for plastics, so the elasticity applying to each separately is higher than the average for manufacturing as a whole. Electronic products, including robots, are inputs into other industries, which will have a higher elasticity of demand as there are competing factors.

Open economy considerations could substantially raise the elasticity of demand in small open economies. The elasticity of demand for a firm that trades is a combination of the domestic elasticity of substitution between manufacturing and non-manufacturing goods, and the elasticity of substitution between domestically-produced and foreign-produced manufacturing goods. The latter is much higher than the former because the predominant manufacturing trade flow is of differentiated products, e.g., German cars versus French cars.

Appendix 1 extends the closed economy model of the preceding section by introducing a foreign manufacturing good that can be bought at constant and exogenous price. The objective is to show how our expression for the



impact of robot price on hours of work, (10), is altered by the introduction of another good that is a close substitute of the domestic good. We do not claim to have an open economy model, which would require much more modelling of the foreign sector. Kiminory Matsuyama (2009) shows that in the open economy the introduction of new technology in one country has ambiguous effects on employment, because the higher productivity that pushes labour to the service sector also improves the country's comparative advantage in international markets. The improvement in international comparative advantage increases demand for the country's exports and this is a positive influence on manufacturing employment that might offset the negative impact of the substitution of labour for robots. Similar results arise here, which we now make explicit within the framework of our model.

We state the main result in the form of a Proposition (see Appendix 1 for proof)

**Proposition 3** *Suppose there is an imported manufacturing good which has elasticity of substitution vis-a-vis the domestic manufacturing good  $\eta > 0$ . If the relative price of the foreign to the domestic manufacturing good is inversely related to the ratio of manufacturing productivities (as in the closed economy model), then in the case of  $\eta = 1$  the elasticity of demand facing domestic producers is the weighted average of  $\varepsilon$  and  $\eta$ , with fixed weights the shares of each product in consumption. If  $\eta \neq 1$ , the weights are not fixed but for as long as  $\eta \geq \varepsilon$ , the introduction of the open economy mitigates (and might reverse) the negative impact of robots on hours of work when robot price falls.*

To make more explicit the result of this Proposition, the model in the Appendix replaces the domestic manufacturing good  $c_1$  in the utility function (4) by

$$\tilde{c}_1 = \left[ \psi c_1^{(\eta-1)/\eta} + (1-\psi) c_1^{*(\eta-1)/\eta} \right]^{\eta/(\eta-1)}, \quad (11)$$

retaining the structure of the rest of the model.  $c_1^*$  is the imported good. In the case of  $\eta = 1$ , the  $\varepsilon$  elasticity in (10) is replaced by  $\psi\varepsilon + (1-\psi)\eta$ , whereas in the case  $\eta \neq 1$ , the left-hand side of the inequality in (10) is more conveniently split into two terms, the one in (10) and a second one that multiplies  $(\eta - \varepsilon)$  by a new positive coefficient that is a function of the parameters of the model. Since  $\eta > \varepsilon$  (see below for evidence), the inequality in (10) is more likely to be satisfied when there is trade than in the closed economy.<sup>13</sup> We summarize some evidence on openness and elasticities here.

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<sup>13</sup>Recall that this extension considers only competition from imports. The introduction of export markets would add another margin of competition that adds another positive term to the left side of (10).

Our sample consists of the United States, the United Kingdom and eleven European Union countries, which trade substantially, so manufacturing exports and imports are high. Table 1 illustrates. Outside the United States, exports of domestically produced goods range from 37.4% of output in the United Kingdom to 76.3% in Belgium, and imports from 26.5% in Italy to 60.2% in Belgium (the United States is an outlier at 16.9% and 19.6% respectively). Their sum exceeds 100% in five of the thirteen countries in the sample.

Jean Imbs and Isabelle Mejean (2010, 2015) estimate import and export elasticities for several countries, ten of which are also included in our sample. In their benchmark estimation, the only elasticity that is below one is for imports into Austria, which is 0.7. For the other countries the range is 1.3 for Belgium to 2.8 for Italy. Export elasticities ranged from 2.6 in Finland to 3.4 in Spain. It is clear that with the openness of our economies and the high elasticity values estimated for imports and exports, the effective elasticity of manufactures facing domestic producers is a high number. For example, even for a large country like France, the demand elasticity for imports is estimated to be 1.74, so if we use its import share of 0.392 as weight, the contribution to the overall manufacturing elasticity coming from imports is 0.686. This is substantially higher than the elasticity of substitution between manufacturing and services estimated for closed economies. In addition there is an impact from the high elasticity of demand for exports. We conclude that existing evidence is consistent with a sufficiently high elasticity of demand for manufacturing output and other non-trivial positive terms being added to the left-hand side of (10) due to foreign trade.

Do countries with a better innovation environment put more weight on the terms on the left-hand side of (10) than countries with a poorer innovation environment? We claim that this is the case because of the connection between the favourable innovation environment, R&D and productivity growth. As Matsuyama (2009) has shown, firms with higher average levels of productivity growth have a comparative advantage in manufactures in international markets (in the notation of the Appendix, because of higher  $A_1/A_1^*$ ), and so trade more. A direct implication of the definition of our innovation index is that firms in countries that rank higher in the innovation index do more R&D and produce more advanced technology products. They are therefore likely to achieve higher rates of productivity growth.<sup>14</sup>

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<sup>14</sup>Countries with a better innovation environment are also characterized by larger robot density, and as Graetz and Michaels (2018) have shown, this improves their productivity. This is another reason for a better comparative advantage in international markets.

## 3.2 Complementary job creation

In this sub-section we return to the closed economy model and discuss factors and evidence that support more complementary job creation in economies with more advanced innovation systems. In our formal model the complementary job creation is shown by a positive  $\beta$ . As Appendix equation (20) shows, at the profit maximizing point, a higher  $\beta$  implies that relatively more workers are employed in the non-automatable part of production. We show that there is a strong correlation between our innovation index and the skills of workers who are not close substitutes to robots, and argue that within the framework of our model, this indicates that in countries with a richer innovation environment firms are operating with higher  $\beta$ . Since a firm has the choice of operating with a lower  $\beta$  by not hiring research or management workers, if they are operating with a higher  $\beta$ , it must mean that the higher  $\beta$  yields higher profit. We show that in the range of  $\beta$  values in which a higher  $\beta$  yields higher profit, the higher  $\beta$  adds more weight on the left-hand side of the inequality in (10); it follows that the higher  $\beta$  in countries with a better innovation environment mitigates the negative employment impact of a lower robot price, or reverses it altogether.

We have argued that by the definition of the innovation environment, countries with a higher innovation index have access to better qualified human capital, more engineers and scientists and are faced with better incentives to undertake R&D. All six indicators that make up the innovation index directly or indirectly point to more R&D activity. Two are directly referring to R&D at the company level. Another two point that in more innovative countries companies are more outwardly-looking and have more collaborations with universities and government. A company that does more R&D or one that is more outward-looking will create tasks for qualified workers that will do the R&D and promote collaborations with universities and government. That more qualified workers are available to take these jobs in countries with higher values of the innovation index is shown in our index by the indicator for the availability of scientists and engineers; in other related indices it is even more explicit. Section 6.3 below discusses other indices, which are highly correlated with our own. All indices of innovation performance pay particular attention to the quality of human capital and the availability of good education and training systems (see also Figure 1). For example, the *Global Innovation Index*, 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.” Better qualified and more sophisticated human capital, and especially one that specializes on methods,

systems, business management, and more directly on R&D, are less substitutable by robots than manual or less well-trained human capital; in terms of our model, their hours of work belong to the complementary tasks in the non-automatable part of production.<sup>15</sup>

It follows from this argument that firms in countries with a more favourable innovation environment should be employing more workers in tasks that are complementary to the production tasks for manufacturing goods. These tasks belong to the category that we called non-automatable; the tasks that better qualified workers are engaged in are not ones that can be done by robots.

In contrast, robots as defined by the International Federation of Robotics, do manual unskilled tasks, such as handling, welding, assembling and dismantling (see the data section 4). The workers that are engaged in these types of tasks are the ones classified as low-skill by databases such as EU KLEMS, which is the one that we use here.

In our data sets, the measures of skills of workers actually employed in manufacturing are not good enough to enable a formal test of the hypothesis that firms in more innovative countries employ more skilled workers.<sup>16</sup> But we give here some correlations that provide strong support for the hypothesis. We use data from EU KLEMS which categorizes workers into three skill types, high, medium and low. There are some missing observations and some inconsistencies (like sudden jumps in the numbers) but taking sample averages makes it possible to construct sample means of workers in each of these categories, except for the United States, which has no available data for skills in manufacturing in our database.<sup>17</sup> Table 2 gives the percentage of high and low skills in the European countries in our sample. The correlations of each with the innovation index are shown in the bottom two rows of the table. The correlations are good for the entire sample and point in the predicted direction, but rise to much higher levels once the two outliers are removed, with +83 for the correlation between the high-skilled group and the innovation index and  $-0.85$  for the correlation of the index with the low-skill group.

We now show that if firms are willing to take on relatively more workers in

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<sup>15</sup>See also International Federation of Robotics, (2018) and Konstantinos Pouliakas (2018). Both these references go further and suggest that robots are complementary to better trained human capital, reaching the conclusion that lifelong learning and upskilling can lead to complementarity between hours and robots.

<sup>16</sup>See also Graetz and Michaels (2018) who faced a similar problem.

<sup>17</sup>There are also two other single observations that are implausible. In the Czech Republic, EU KLEMS has a very low entry for low-skill workers and a very high one for medium-skill ones, and in Spain the number of highly skilled workers is implausibly high, at the expense of medium skilled workers.

complementary tasks, they might increase (or reduce by less) overall employment when the price of robots falls. Firms are willing to take on workers in complementary tasks if a higher  $\beta$  does not reduce profit. By differentiation of the profit function of the firm at the profit-maximizing point, Appendix 1 shows that a higher  $\beta$  does not reduce profit if  $\beta$  is in the range given by

$$1 > \beta \geq \beta_0 = \frac{\alpha q^{1/s}}{1 + \alpha q^{1/s}}. \quad (12)$$

To give some more information about this range, we note that Appendix equation (23) implies that at  $\beta = \beta_0$ , robot density is given by

$$\frac{R}{H_1} = (1 - \alpha)^{-s/(s-1)} \frac{(q^{(s-1)/s} - \alpha)^{s/(s-1)}}{1 + q}, \quad (13)$$

where now  $q$  is the value taken by the relative employment levels  $H_{1N}/H_{1R}$ . There is no data that can be used to inform the actual ratio  $H_{1N}/H_{1R}$  in manufacturing, or the value of parameter  $\alpha$ , so we do not have information about  $\beta_0$ . But since robot density falls in  $\beta$ , restricting  $\beta$  to the range  $\beta \geq \beta_0$ , is equivalent to restricting robot density to a range below the one in (13). To obtain a rough measure of the critical value of robot density in (13), we used parameter values  $\alpha = 0.3$ ,  $s = 3.8$  and  $\rho = 1$ . Since  $\alpha$  is the share of labour in the automatable part of production, it should be a small number, even below the 0.3 that we selected (lower  $\alpha$  gives higher critical value for density). The elasticity  $s$  is from Cheng et al. (2021), the only study that we could find that estimates substitution elasticities in the automatable part of production (for Chinese industries) and  $\rho$  is the relative price of one hour of robot work to one hour of labour input. We selected unity in the absence of good data on the flow inputs (data on prices for robots do of course exist but they do not take into account the time that robots are operating or the cost of running and maintaining them). The values obtained for the critical density were so far in excess of observed densities, even in Germany, that small variations in parameters would not violate the assumption that the range of  $\beta$  is within the values shown in (12).

Referring now to condition (10), which needs to be satisfied for an increase in equilibrium hours when the price of robots falls, we find that its left side is a rising function of  $\beta$  when  $\beta \geq \beta_0$ . So, provided that  $\varepsilon > \sigma$ , the inequality is satisfied over a bigger range of parameters at higher  $\beta$ . This establishes our main result for the role of complementary task creation in robot-using sectors of the economy.

**Proposition 4** *If it is profitable for the firm to operate at a higher value of  $\beta$  because of the availability of more scientists and engineers and other highly qualified workers, then, provided the elasticities are such that  $\varepsilon > \sigma$ , lower robot price yields either a positive or a smaller negative impact on hours of work.*

## 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 and sources for national innovation systems.<sup>18</sup> We use annual observations of the innovation index, although it is a slow-changing index and there are no country reorderings during the sample period. In the sample means Table 3, three countries stand out as having the lowest index values for innovation, 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 includes Germany, Sweden, Finland and the United States. The mean value of the index is 4.85, with France approximately in the middle, four other countries below it and the rest above it.

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, from the earliest year for which we have complete data sets for industrial robots and the innovation index, to the most recent year of the EU KLEMS data. We focus mainly on seven manufacturing sectors but we also include three non-manufacturing sectors in some of the tests. We have consistent data from thirteen industrial countries with some missing observations, especially in the early years. The list of countries and sectors, with sample means, are shown in Tables 2 and 3.<sup>19</sup>

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<sup>18</sup>Appendix 2 gives more details on sources and the construction of variables.

<sup>19</sup>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 average number of manufacturing robots (one sixth of 1%). In addition to the countries that we use here, we compiled data for Greece and Slovakia. Both countries are small uses of robots that turned out to be outliers when compared with the rest, with a big impact on results, so we removed them from our final sample.

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).<sup>20</sup>

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. ICT capital turned out to be statistically insignificant in our key regressions and we did not include it as a separate capital variable in the reported results.

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 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.

There are large differences in robot density, both across countries and across industries (Tables 3 and 4). 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 lowest value for innovation capacity. Given the relatively high robot density in the manufacture of transport equipment, 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. Non-manufacturing sectors are very low users of robots when compared with manufacturing, so we do not make them part of our core regressions. We do test, however, for their consistency with manufacturing.

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<sup>20</sup>When countries calculate their own operational stock the IFR uses that figure instead.

## 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:

$$\ln H_{ict} = \beta_0 + \beta_1 \ln(R_{ict}/H_{ict}) + \beta_2 \ln(R_{ict}/H_{ict}) * V_{ct} + Z_{ict} + \varepsilon_{ict} \quad (14)$$

$H_{ict}$  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, and country and year fixed effects;  $\varepsilon_{ict}$  is the error term. We have tested for other labour market variables, such as the capital stock classified as ICT by EU KLEMS, but they were not significant.

It is not possible to derive an explicit equation of this kind from our model, mainly because of the split in hours of work between the automatable and non-automatable parts of production. This split is not empirically observed, although skill, had there been good data at the level of this analysis, could have been used as a way to discriminate between them somewhat. Appendix equation (18) is an equation in non-automatable hours in terms of the variables on the right-hand side of (14), and equation (17) is a similar equation for the automatable part of hours. When the two are added and log-linearized they yield an equation of the kind that we estimate, although the estimated coefficients do not have counterparts in the model, except for net effects. We follow the tradition of earlier literature and we look for robust estimates of these net effects that enable us to make inferences about the model.

A key claim of our model is that the country response of industrial hours to the introduction of robots varies, 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 net 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  $\beta_1$  to be negative but that of  $\beta_2$  to be positive. The Appendix equations referred to in the preceding paragraph make the key independent variable robot density in the automatable part of production; since we do not have data for hours in the automatable part of production, we follow the literature and write robot density in terms of all



hours (e.g., Graetz and Michaels, 2018). An alternative specification is to specify the right-hand side variable in levels. We estimated the same regressions for levels and results were similar to the ones with density for the key net elasticity estimate. They are reported briefly in section 6.

We estimate equation (14) 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 5 shows the results of the estimation of the basic equation (14) for the seven manufacturing sectors. We separated transport equipment and electronics from the rest of manufacturing. 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 could not be separated out. We refer to their aggregate as low-tech. We tested for equality of the estimated coefficients across the three industrial groups, with a view to aggregating them into a single manufacturing sector, but equality was strongly rejected, by an  $F$  test that gave  $F(4, 946) = 37.5$ .

Consider first results for the simple regression without taking into account the innovation system of the country. In column (1) of Table 5, the impact of robot density on hours of work is negative but not significant for the transport equipment industry and positive for electronics and the rest of manufacturing. In addition to robot density and country and time fixed effects, we include two other economic variables, the capital stock, and the total wage bill for the industrial sector divided by hours of work. The elasticities of the two 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 0.65, and the hourly wage elasticity is  $-0.39$ .

In column (3) we estimate the same 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, and it is the country with the largest robot densities in manufacturing worldwide. The choice of instrument was dictated by the Cragg-Donaldson

Wald  $F$  statistic, which gave a higher value for this instrument than the alternatives tested (see below). The results of the IV regression show substantial changes in the point estimates of the coefficients, and there is a sign reversal for transport equipment.

So overall, the conclusion from the estimation of equation (14) for manufacturing, under the restriction  $\beta_2 = 0$ , is that although across countries there is on average a positive impact of robot density on hours of work in the electronics and low-tech industries, and an imprecise impact for transport equipment, they are not robust across estimation specifications. The same can be said for the coefficient on wages, which drops substantially in the IV estimation.

In column (2) of Table 5 we show OLS estimates when the innovation environment is taken into account. The coefficient estimates have the expected sign, with  $\beta_1$  negative and  $\beta_2$  positive for all industries. This indicates that in countries with higher index value for innovation, the impact of robots on hours of work is either weaker negative or positive. The point estimates bring out more contrasts between the industrial sectors. We highlight two of these differences, one for electronics and one for transport equipment.

In electronics the innovation environment plays a more important role than in other sectors, driving more substitutions between robots and hours at both the weakest and strongest countries. The difference in the net coefficient ( $\beta_1 + \beta_2 V_{ic}$ ) between the most innovative and the least innovative countries (United States and Italy, respectively) is 0.387 for electronics but only 0.067 for transport equipment and 0.111 for the non-tech industries. This is to be expected, as electronics is the most research-driven industrial sector in manufacturing. It is also a producer of new technologies, including robots. By its definition, the innovation environment is important in driving research. In this sector, the point at which the sign of the net impact of robot density on hours switches from negative to positive is at  $V_{ct} = 4.40$ , which is below the sample mean. The significance of this point is further discussed further down in this section with reference to Table 6.

In contrast to electronics, the transport equipment industry is not very sensitive to the innovation environment. The point at which the sign of the net impact of robot density on hours switches is at  $V_{ct} = 5.05$ , above the sample mean, and its impact in driving differences between countries, although statistically significant, is small. 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 as many new jobs in complementary tasks. A favourable innovation environment in the country still saves some jobs from replacement by robots in this sector, but it does not yield net job

creation.

The low-tech industries fall between the two high-tech sectors. We discuss further the net coefficients in all industries later in this section, when we report both point estimates and standard errors for net effects.

The instrumental variables estimation of the regression with the innovation index is in column (4) of Table 5. The results confirm an even stronger influence of the innovation index on the impact of robots on hours in all three sectors. In the two high-tech sectors the coefficient on the non-interactive term falls, but because of the larger estimate on the interactive term, the value of the index at which the net coefficient switches from negative to positive is lower than in the OLS estimates. In the low-tech industries the impact of the innovation index is also higher, through a larger coefficient estimate for the interactive term. Overall, the IV estimation confirms a large role for the innovation environment in determining the impact of robot density on hours of work.

In order to gain more information on the role of the innovation environment, in Table 6 we estimate the net elasticities at sample means implied by the OLS estimate for all countries, with their robust standard errors. The importance of the innovation environment comes out clearly in the electronics sector. In Italy and Spain, the poorest innovation countries, the net effect of robot density on hours is negative and statistically significant, but with the exception of the Czech Republic, in which it is statistically insignificant, in all other countries the net coefficient on robot density is positive and statistically significant. In contrast, in the transport equipment industry the net impact of robot density is negative and statistically significant in the three weakest countries and in all the others there is no statistically significant effect on hours.

The results for low-tech industries are perhaps surprising, because in no industry is the impact of robot density on hours of work negative and significant, whereas with the exception of the weakest three countries, all other countries have statistically significant and positive net effects. But the impact of the innovation environment is not very strong, in the sense that the rise in the point estimate of the net effect as we move from less to more innovative countries is small.

The IV results give similar conclusions about net effects but point estimates differ somewhat. Overall, the IV results give a stronger impact of the innovation environment, and make the positive effects stronger, especially in the low-tech sectors.

We shed more light on the quantitative importance of these estimates by calculating the implied change in hours of work due to robot density between two sub-periods of the sample, from the average of 2011-13 to the

average of 2014-16. We selected these periods to avoid cyclical effects due to the financial crisis. There is a trend decline in manufacturing employment throughout the sample period, which in the estimation is picked up by time dummies. The estimates reported in Tables 5 and 6 detrend the data by entering a  $(0, 1)$  dummy variable for each year in the sample. Results were virtually identical when a single time trend was introduced instead, and also when the time trend was interacted either with the industry dummies or with the country dummies. This is perhaps surprising, given the large cyclical fluctuations due to the financial crisis, which are picked up by the yearly dummies but not by the single time trend. However the estimates on each time dummy are not significantly different from the single estimate on the time trend.

In order to obtain more accurate quantitative measures of the impact of robot density on hours of work we detrended the series for each industry by using the coefficient estimated for a time trend specific to each industry. These coefficients are, respectively,  $-0.029$ ,  $-0.022$  and  $-0.081$  for electronics, transport equipment and low-tech industries. We report the results for three representative countries only to save space, the two countries at the extremes of the innovation index, Italy and the United States and a major economy closer to the middle, Germany. The results are shown in Table 7. All the net coefficient estimates used, taken from Table 6, are significantly different from zero except for the three shown with an asterisk in Table 7, two for transport equipment and one for low-tech industries.

In all cases except for low-tech industries in Italy, in which the net coefficient estimate is not significantly different from zero, the predicted change is in the direction of the actual change. Looking at electronics first, the contrast between Italy and Germany reveals an interesting pattern: In Italy it went down by 31.5 hours, 10.9 of which are accounted for by robot substitutions, whereas in Germany it went up by 31.3 hours, 10.7 of which are accounted for by robot substitutions. In the United States hours of work in this industry also increased but not by as much as is predicted by the rise in robot density. Robot density in this country increased very fast in recent years and this increase is not reflected in a very fast increase in hours of work, which is predicted by its high innovation index. In the other two sectors the change in the detrended series is closer to the prediction obtained from the change in robot density, although the point estimate in the transport equipment industry is not statistically different from zero at the 5% level. We note that since the other economic variables in the regression are the capital stock and wages, the remainder of the change in hours is either in the unexplained residual or the result of changes in wages or the capital stock.

Actual and predicted changes in the other two sectors in Germany and

Italy are also in the same direction and reasonably close to each other, except for the two estimates that are not significantly different from zero. The Italian estimate for transport equipment is quite interesting, in the sense that the detrended series went up by 4.9 million hours, virtually all of which is explained by a fall in robot density in that sector during this period.

## 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 1995 to 2005 and robot density in Japan from 2006 to 2016. The justification is similar to our preferred instrument of robots in Korea. Germany is the country in our sample with the biggest robot penetration in its manufacturing and has good data going back to 1995. Since the price of robots has been falling long before our sample begins (IFR, 2017), any correlations between the German trends before 2005 and our sample are likely to be due to technological improvements in robot production, as reflected in their price. Our third instrument, robots in Japan, is another signal of technology trends across industries. Japan is a big user of robots and the world's leading supplier of industrial robots. Like Korea, it is sufficiently removed from our sample of Europe and the United States to be less influenced by other shocks in industrial hours in the countries of our sample.

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 positive in the regression without industry dummies but it became completely insignificant when industry dummies were introduced. This is more evidence that without the innovation index the estimation results are sensitive to small changes in the specification. In contrast, in the regression with the innovation index the estimates with the two new instruments were very similar to the IV estimation in Table 5. As before, instrumentation of the regression that includes the innovation index shows more robustness than the one without the index, confirming the point estimates in Table 5.

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 very similar to the regressions without industry dummies. In the first three columns of Table 8 we report the results with industry dummies either individually or interacted with country and time effects, for the regressions with the interactions with

the innovation index. These estimates should be compared with the second column estimates of Table 5 for robustness. It is clear from this comparison that the results are virtually identical in all cases.

We tried one other specification, two-way clustering with 77 industry/year clusters. The results are shown in the final column of Table 8 and again they should be compared with the second column of Table 5. Estimates are very close to each other for all coefficients.

## 6.2 Sample exclusions

With seven industrial sectors and thirteen countries, mostly small European ones, it is possible that single important sectors or countries drive the results. Given our split of manufacturing into three groups, there are no single important sectors within groups that might drive the results. But across geographies, Germany is a large country and by some margin the biggest user of robots in its manufacturing (see Table 3). We re-estimated our main regression by excluding Germany but this made virtually no difference to the estimated coefficients in Table 5. This is consistent with the fact that Germany is fairly close to the mean of the innovation index distribution, at which point the impact of robots on hours of work is small.

## 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 0.86 and with the European index (excluding the United States) 0.93. 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 5. In the interests of space we do not report the estimated regressions but give here only some key coefficients for the net effects. Statistical significance for the point estimates is comparable to that for the regressions in Table 5.<sup>21</sup>

Table 9 gives the net elasticity estimates for the least innovative country (Italy) and the most innovative one (the United States in our index and the *Global Innovation Index* or Sweden for the European Union index, which in the absence of the United States is the most innovative country). The estimates for our index are taken from Table 6. It is clear that with minor exceptions, our estimates can be replicated with alternative indices for a country's innovation environment and they are not due to any 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.

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<sup>21</sup>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.

## 6.4 Non-manufacturing industries

Table 10 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 a common industry fixed effect for non-manufacturing, although the results are virtually identical with a full set of manufacturing and non-manufacturing fixed effects. We show only OLS results, as the instrumental variable estimates were not very precise. The general message, however, in the IV estimates was the same as the one shown in the OLS regression.

Hours of work in the non-manufacturing sectors are large, being more than a third of manufacturing hours, and dominated by agriculture. Robot density in agriculture is less than one-tenth of the least robotized manufacturing sector, and there are several zero entries in the sample, which force us to discard several observations from our manufacturing sectors as well. So it is not surprising to find that the results do not replicate very precisely the results that we obtained in Table 5 for manufacturing. Our main finding is replicated, namely that the innovation environment of a country is an important influence on the impact of robotics on hours of work in manufacturing. But the point estimates give much more importance to the innovation environment than is shown in our estimates in Table 5.

The result that we consistently derive for non-manufacturing is that the innovation environment has no influence on the impact of robots on hours. This is not surprising, given the low robot density and low research potential in these sectors. The net impact of robot density on hours that we estimate is negative, i.e., the introduction of robots unambiguously reduces hours in non-manufacturing in all our countries. The coefficient estimate is robust to the introduction of the innovation index, which has very large standard error when included in the estimation. It is at about the level estimated for the countries with the weakest innovation environment in the manufacturing sector, with the strongest negative substitutions (Italy and transport equipment). So overall, non-manufacturing sectors experience stronger substitutions than any of the manufacturing sectors in any country.

## 6.5 Decomposing the innovation index

Our final robustness test for robot density is a very stringent one that breaks up the innovation index into its six components and runs the OLS regression in column (2) of Table 5 again, with each replacing the national innovation



index. It is stringent because our innovation index might average out any fluctuations in a single pillar, which will influence the estimation in this decomposition. The coefficient estimates are in Table 11.

All indicators except for the availability of scientists and engineers give statistically significant results that conform to the estimates of Table 5. 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.

## 6.6 Level of robots

Finally, we report the main regressions in Table 5 when robot density in (14) is replaced by the log of the number of robots. The results are in Table 12. The main message comes through in the sense that a good innovation environment acts to mitigate, or reverse, any negative impact of robots on hours of work. This result is statistically significant in both the OLS estimates and the IV estimates. But a difference in the point estimates that runs through all regressions in Table 12 is that the impact of robots on hours is not statistically significant negative even in the countries with the weakest innovation systems. For example, none of the estimated robot coefficients on hours in Italy is significantly different from zero, whereas in countries with stronger innovation environments it is positive in all cases. When estimated with the level of robots, our model implies less substitution between robots and hours of work than when estimated with robot density.

## 7 Conclusions

Our argument in this paper is that as emphasized by many authors, robots have the technical capabilities to replace humans in manufacturing and some other sectors; but whether they do or not depends 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 human capital, the quality of scientific research and the collaboration between companies, universities and governments, play a critical role in shaping those incentives. Countries with a poor innovation environment, mainly located in the European South and East, on average 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.

Some notable and intuitive differences between sectors have been identified. In electronics and electrical equipment, the innovation environment plays a more important role than in other sectors. This is intuitive because this sector is among the main research sectors, being also a producer of robots. In this sector countries with a more favourable innovation environment increase hours of work when more robots are employed. In contrast, transport equipment, which is the biggest user of robots, substitutes robots for hours more than other sectors. There is no country with more hours when robot density in this sector is higher, but there are some with strong and statistically significant substitutions.

In predictions with the manufacturing estimates, we were able to show that the adoption of more robots during our sample period can explain large parts of the detrended changes in manufacturing employment. For example, hours of work in German electronics are shown to be above trend and in Italy they are below trend, by about the same percentage. About one third of this divergence from trend in each country is explained by the adoption of robots, in Germany increasing hours because of its favourable innovation environment and in Italy decreasing them because of its unfavourable innovation environment.

We find strong substitutions as well in non-manufacturing production sectors. We tested the impact of robot density in three sectors, agriculture, mining and utilities, which are very small users of robots, and found that the innovation environment played no role in these sectors. They consistently used robots to replace human labour, with a higher negative elasticity than the one estimated for transport equipment in the countries with the weakest innovation environments.

We have rationalized these results in a model in which the firm creates two types of jobs. One type is engaged in tasks that can also be done by robots and one engaged in tasks that are complementary to the output of robots. For example, welding can be done by both humans and robots but research or managerial work is done by humans and it complements the output of the production part of the firm, in which robots are engaged. In this model, whether robots replace or complement labour depends on the relation between three elasticities, the elasticity of the demand for the final product and the two elasticities of substitution between the two types of human tasks and robots.

We have argued that there are two channels in this framework that justify the claim that a more favourable innovation environment is associated with higher robot density and hours of work. The first is based on the open economy. Countries that engage more in innovation gain a comparative advantage in international markets for manufactures and through trade ex-

perience a higher elasticity of demand for their final products. Germany and the United States might fit this argument. The second is partly based on the special features of an innovative country, such as engagement in more R&D and the availability of better qualified human capital, which make it easier for them to create complementary tasks when robots are introduced. The Nordic countries might fit this scenario, in contrast to countries like Italy and Spain, which do not create enough complementary tasks when robots replace labour in competing tasks.

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 1. Derivations

The profit of the firm in sector 1 is

$$\Pi = p_1 Y_1 - \rho W R - W(H_{1R} + H_{1N}), \quad (15)$$

with  $Y_1$  given by (2) and (1). The maximum satisfies the marginal productivity conditions,

$$p_1 A_1 (1 - \beta) \left( \frac{Y_1}{A_1 F} \right)^{1/\sigma} (1 - \alpha) \left( \frac{F}{R} \right)^{1/s} = \rho W, \quad (16)$$

$$p_1 A_1 (1 - \beta) \left( \frac{Y_1}{A_1 F} \right)^{1/\sigma} \alpha \left( \frac{F}{H_{1R}} \right)^{1/s} = W, \quad (17)$$

$$p_1 A_1 \beta \left( \frac{Y_1}{A_1 H_{1N}} \right)^{1/\sigma} = W. \quad (18)$$

Dividing (16) by (17) we get the robot density in the automatable part of production,

$$\frac{R}{H_{1R}} = \left( \frac{1 - \alpha}{\alpha \rho} \right)^s \equiv r. \quad (19)$$

Clearly, lower robot price leads to a rise in robot density. In the derivations in this Appendix, it is convenient to use  $r$  in place of the exogenous price  $\rho$ , given that we always treat  $\alpha$  and  $s$  as fixed parameters. We refer to a rise in  $r$  as equivalent to a fall in the exogenous price of robots.

Dividing (17) by (18) we get,

$$\frac{H_{1N}}{H_{1R}} = \left( \frac{\beta}{1 - \beta} \right)^\sigma \alpha^{-\sigma} q(r)^{(s-\sigma)/s}, \quad (20)$$

with  $q$  defined by,

$$q(r) \equiv [\alpha + (1 - \alpha)r^{(s-1)/s}]^{s/(s-1)}, \quad q'(r) > 0. \quad (21)$$

The function  $q(r)$  is another uniquely defined function of  $\rho$ , given the fixity of  $\alpha$  and  $s$ . Higher  $r$  (lower robot price) raises  $H_{1N}/H_{1R}$  under the restriction  $\sigma < s$ .

Robot density in sector 1 is given by

$$\frac{R}{H_1} = \frac{R}{H_{1R}} \frac{1}{1 + H_{1N}/H_{1R}}, \quad (22)$$

or alternatively,

$$\frac{R}{H_1} = \frac{r}{1 + \left(\frac{\beta}{1-\beta}\right)^\sigma \alpha^{-\sigma} q(r)^{(s-\sigma)/s}}. \quad (23)$$

**Result 1.** *Robot density rises with  $r$*

Differentiation of (23) with respect to  $r$  shows that the sign of the partial is the same as the sign of

$$1 + \left(\frac{\beta}{1-\beta}\right)^\sigma \alpha^{-\sigma} q(r)^{(s-\sigma)/s} \left(1 - \frac{s - \sigma}{s} \frac{r q'(r)}{q}\right). \quad (24)$$

The elasticity of  $q(r)$  is,

$$\frac{r q'(r)}{q} = \frac{(1-\alpha)r^{(s-1)/s}}{\alpha + (1-\alpha)r^{(s-1)/s}} < 1, \quad (25)$$

which establishes the result, given  $0 < \sigma < s$ .

We note that this result was derived from the first-order conditions of the firm's maximum, without making use of the equilibrium conditions.

**Result 2.** *Hourly productivity rises with  $r$ .* Making use of conditions (19) and (20), we get,

$$F = q(r)H_{1R}, \quad (26)$$

$$Y_1 = A_1 H_{1N} \beta^{-\sigma} X^{\sigma/(\sigma-1)}, \quad (27)$$

$$X \equiv (1-\beta)^\sigma \alpha^{\sigma-1} q(r)^{(\sigma-1)/s} + \beta^\sigma. \quad (28)$$

Hourly productivity  $Y_1/H_1$  is given by

$$\frac{Y_1}{H_1} = A_1 \frac{H_{1N}}{H_1} \beta^{-\sigma} X^{\sigma/(\sigma-1)}, \quad (29)$$

which by differentiation with respect to  $r$ , given the expressions in (23), (21) and (28) gives the result. The restriction  $s \geq \sigma$  is sufficient for this result but not necessary.

To complete the demonstration of the results in Proposition 1 we need to complete the equilibrium, as prices are equilibrium outcomes. The equilibrium is completed by the marginal rate of substitution between the two

goods obtained from the consumer maximization and the firm's marginal productivity condition in sector 2,

$$\frac{p_1}{p_2} = \frac{\omega}{1-\omega} \left( \frac{c_1}{c_2} \right)^{-1/\varepsilon} = \frac{\omega}{1-\omega} \left( \frac{Y_1}{Y_2} \right)^{-1/\varepsilon} \quad (30)$$

$$p_2 A_2 = W \quad (31)$$

We simplify the expressions by dividing (18) by (31), and then using (27) to substitute out  $Y_1$ , we get

$$\frac{p_1 A_1}{p_2 A_2} X^{1/(\sigma-1)} = 1. \quad (32)$$

**Result 3.** *Relative prices  $p_1/p_2$  fall with  $r$ .* Differentiation of (32) immediately yields the result

This completes the proof of Proposition 1. To prove now the statements in Proposition 2, we make use of the production functions for sectors 1 and 2, (27) and (3), and the consumption MRS condition (30), to obtain,

$$\frac{p_1 A_1}{p_2 A_2} = \frac{\omega}{1-\omega} \left( \frac{A_1}{A_2} \right)^{(\varepsilon-1)/\varepsilon} (\beta X^{-1/(\sigma-1)})^{\sigma/\varepsilon} \left( \frac{H_{1N}}{H_2} \right)^{-1/\varepsilon}. \quad (33)$$

Equations (32), (33) and (20) give, after simple substitutions,

$$\frac{H_{1N}}{H_2} = A \beta^\sigma X^{(\varepsilon-\sigma)/(\sigma-1)}, \quad (34)$$

$$\frac{H_{1R}}{H_2} = A(1-\beta)^\sigma \alpha^\sigma q(r)^{(\sigma-s)/s} X^{\frac{\varepsilon-\sigma}{\sigma-1}}, \quad (35)$$

with  $A$  defined by productivity and preference constants that play no further role in our analysis,

$$A = \left( \frac{\omega}{1-\omega} \right)^\varepsilon \left( \frac{A_1}{A_2} \right)^{\varepsilon-1}. \quad (36)$$

Given now that  $H_1 = H_{1N} + H_{1R}$ , we obtain from (34) and (35) the ratio of hours of work in the two sectors,

$$\frac{H_1}{H_2} = A[(1-\beta)^\sigma \alpha^\sigma q(r)^{(\sigma-s)/s} + \beta^\sigma] X^{\frac{\varepsilon-\sigma}{\sigma-1}}, \quad (37)$$

which, together with (6) solves for the labour allocations in the two sectors.

**Result 4.** *For  $\beta = 0$ , the condition  $s > \varepsilon$  implies that  $H_1$  falls when  $r$  rises; it rises with  $r$  if  $s < \varepsilon$ .* From (34)-(35), when  $\beta = 0$ ,  $H_1 = H_{1R}$  and from (28),

$$X = \alpha^{\sigma-1} q(r)^{(\sigma-1)/s}. \quad (38)$$



Therefore,

$$H_1 = H_{1R} = A\alpha^{\sigma-1}q(r)^{(\varepsilon-s)/s}, \quad (39)$$

which delivers the result.

**Result 5.** *For  $\beta > 0$ , a sufficient condition for a fall in  $H_1$  when  $r$  rises is  $\sigma \geq \varepsilon$ . If  $\sigma < \varepsilon$  there are two conflicting effects on  $H_1$ , a negative one due to  $s > \sigma$  and a positive one due to  $\varepsilon > \sigma$ .*

Equation (37) has two terms, the one in the square brackets and  $X^{\frac{\varepsilon-\sigma}{\sigma-1}}$ . Differentiating each separately delivers the result. The explicit condition for a net positive effect is shown in equation (10) in the main text.

## 8.1 Imports

Suppose that consumers have the choice of two manufacturing goods, one produced domestically as in the main text and an imported good  $c_1^*$ , which has elasticity of substitution with the domestic good  $\eta > 0$ . The consumer maximization problem is

$$\max_{c_1, c_1^*, c_2} U(c) = \ln \left[ \omega \tilde{c}_1^{(\varepsilon-1)/\varepsilon} + (1-\omega)c_2^{(\varepsilon-1)/\varepsilon} \right]^{\varepsilon/(\varepsilon-1)} \quad (40)$$

$$\tilde{c}_1 = \left[ \psi c_1^{(\eta-1)/\eta} + (1-\psi)c_1^{*(\eta-1)/\eta} \right]^{\eta/(\eta-1)} \quad (41)$$

$$\sum_{i=1}^2 p_i c_i + p_1^* c_1^* \leq Y. \quad (42)$$

We assume  $0 < \omega < 1$  and  $0 < \psi \leq 1$ , allowing for the case of the closed economy when  $\psi = 1$ .

The production side of the economy is the same as before, except for one small change in sector 1 that makes no difference to the results derived here, but it shows how exports might be introduced in an extended model. The firm still sells all its output at price  $p_1$ , with  $c_1$  bought and consumed domestically, but another part  $c_1^{**}$  is bought by an exogenous agent. We assume that  $c_1^{**} = (1-k)Y_1$ , i.e., that the exogenous demand is a fixed fraction of output, with  $k \in [0, 1)$ . The market clearing condition in sector 1 then becomes,  $c_1 + c_1^{**} = Y_1$ , or simply

$$c_1 \leq kY_1, \quad (43)$$

which replaces the first inequality of (8). Everything else on the production side remains the same as before, including all elasticities,  $\varepsilon$ ,  $\sigma$  and  $s$ .

It follows that Results 1 and 2 hold as before. The only real change with the introduction of imports comes from a new condition for consumption

allocations, replacing (30). The new marginal rate of substitution conditions are,

$$\frac{c_1}{c_1^*} = \left( \frac{\psi}{1-\psi} \right)^\eta \left( \frac{p_1}{p_1^*} \right)^{-\eta} \quad (44)$$

$$\frac{\tilde{c}_1}{c_2} = \left( \frac{\omega}{1-\omega} \right)^\varepsilon \left( \frac{\tilde{p}_1}{p_2} \right)^{-\varepsilon} \quad (45)$$

$$\tilde{p}_1 = [\psi^\eta p_1^{1-\eta} + (1-\psi)^\eta p_1^{*1-\eta}]^{1/(1-\eta)} \quad (46)$$

From these we get,

$$\frac{c_1}{c_2} = \left( \frac{\tilde{c}_1}{c_1} \right)^{-1} \left( \frac{\tilde{c}_1}{c_2} \right) \quad (47)$$

$$= \left( \frac{\tilde{c}_1}{c_1} \right)^{-1} \left( \frac{\omega}{1-\omega} \right)^\varepsilon \left( \frac{\tilde{p}_1}{p_2} \right)^{-\varepsilon} \quad (48)$$

$$= \left( \frac{\omega}{1-\omega} \right)^\varepsilon \left( \frac{p_1}{p_2} \right)^{-\varepsilon} \left( \frac{\tilde{p}_1}{p_1} \right)^{-\varepsilon} \left( \frac{\tilde{c}_1}{c_1} \right)^{-1} \quad (49)$$

$$= \left( \frac{\omega}{1-\omega} \right)^\varepsilon \left( \frac{p_1}{p_2} \right)^{-\varepsilon} \psi^{-\eta} \left( \frac{\tilde{p}_1}{p_1} \right)^{\eta-\varepsilon}, \quad (50)$$

which is the generalization of (30), written in more comparable form as,

$$\frac{p_1}{p_2} = \frac{\omega}{1-\omega} \psi^{-\eta/\varepsilon} \left( \frac{\tilde{p}_1}{p_1} \right)^{(\eta-\varepsilon)/\varepsilon} \left( \frac{c_1}{c_2} \right)^{-1/\varepsilon}. \quad (51)$$

Going through the same substitutions as the ones that gave (33)-(37), we find that the relative employment levels are given by

$$\frac{H_1}{H_2} = A[(1-\beta)^\sigma \alpha^\sigma q(r)^{(\sigma-s)/s} + \beta^\sigma] X^{\frac{\varepsilon-\sigma}{\sigma-1}} \left( \frac{\tilde{p}_1}{p_1} \right)^{\eta-\varepsilon}, \quad (52)$$

where now,

$$A = \left( \frac{\omega}{1-\omega} \right)^\varepsilon \left( \frac{A_1}{A_2} \right)^{\varepsilon-1} \frac{1}{k\psi^\eta}. \quad (53)$$

The new term in (52) is the “terms of trade” effect,  $\tilde{p}_1/p_1$ . Without a model for foreign sector equilibrium we assume, in parallel with our earlier result for domestic prices (32), that the ratio of foreign to domestic prices is equal to the inverse of the ratio of sector productivities:

$$\frac{p_1^*}{p_1} = \frac{A_1}{A_1^*} X^{1/(\sigma-1)}. \quad (54)$$

The numerator is the productivity of the domestic sector 1, with  $A_1$  representing the neutral component and  $X^{1/(\sigma-1)}$  the component originating in the automatable part of sector 1 production. The denominator is the exogenous rest-of-world manufacturing productivity, which in general would include non-neutral components due to robots and other capital in the rest-of-world economy, but which we assume to be exogenous here. It follows that

$$\begin{aligned}\frac{\tilde{p}_1}{p_1} &= \left[ \psi^\eta + (1-\psi)^\eta \left( \frac{p_1^*}{p_1} \right)^{1-\eta} \right]^{1/(1-\eta)} \\ &= \left[ \psi^\eta + (1-\psi)^\eta \left( \frac{A_1}{A_1^*} \right)^{1-\eta} X^{(1-\eta)/(\sigma-1)} \right]^{1/(1-\eta)}\end{aligned}\quad (55)$$

and so  $\partial \frac{\tilde{p}_1}{p_1} / \partial q > 0$ . It follows from (52) that the introduction of competition from imports for domestic producers adds another impact term on  $H_1/H_2$  when robot price falls [or  $q(r)$  increases], which is equal to  $(\eta - \varepsilon)$  times a positive expression derived from the differentiation of (55).

A special case arises when  $\eta = 1$ . In that case (55) becomes,

$$\begin{aligned}\frac{\tilde{p}_1}{p_1} &= \psi^{-\psi} (1-\psi)^{1-\psi} \left( \frac{p_1^*}{p_1} \right)^{1-\psi} \\ &= \psi^{-\psi} (1-\psi)^{1-\psi} \left( \frac{A_1}{A_1^*} \right)^{1-\psi} X^{(1-\psi)/(\sigma-1)}\end{aligned}\quad (56)$$

and so (37) simplifies to

$$\frac{H_1}{H_2} = A[(1-\beta)^\sigma \alpha^\sigma q(r)^{(\sigma-s)/s} + \beta^\sigma] X^{\frac{\psi\varepsilon+1-\psi-\sigma}{\sigma-1}},\quad (57)$$

with  $A$  now also including the constants in (56). From this it immediately follows that the elasticity difference term on the left side of (10) changes from  $(\varepsilon - \sigma)$  to  $(\psi\varepsilon + 1 - \psi - \sigma)$ . As  $\psi$  in this case is the share of domestic goods in consumption, the expression  $(\psi\varepsilon + 1 - \psi)$  is the weighted average elasticity of domestic and foreign goods consumed [ $\psi\varepsilon + (1-\psi)\eta$  for  $\eta = 1$ ]. For values of  $\eta \neq 1$ , however, the combination of the elasticities is non-linear, as in (55), and it is not possible to write a simple expression like the one in (57) for  $H_1/H_2$ .

We finally note that if the exogenous “foreign” demand for output,  $1 - k$ , increases, it is shown by a fall in  $k$  and so through (53) and (52) a rise in  $A$  and  $H_1/H_2$ , giving another reason for complementary job creation.

## 8.2 Complementary job creation

In order to find the partial derivative of output with respect to  $\beta$ , differentiate (2) to get,

$$\frac{\partial Y_1}{\partial \beta} \frac{1}{Y_1} = \frac{\sigma}{\sigma - 1} A_1^{(\sigma-1)/\sigma} \left[ (1 - \beta) \left( \frac{F}{Y_1} \right)^{(\sigma-1)/\sigma} + \beta \left( \frac{H_{1N}}{Y_1} \right)^{(\sigma-1)/\sigma} \right]^{\sigma/(\sigma-1)}. \quad (58)$$

Making use of the first-order conditions (16)-(18), to substitute out the fractions in the square brackets, we get,

$$\frac{\partial Y_1}{\partial \beta} \frac{1}{Y_1} = \frac{\sigma}{\sigma - 1} (A_1 p_1 W)^{\sigma-1} \left[ \beta^{\sigma-1} - ((1 - \beta) \alpha q(r)^{1/s})^{\sigma-1} \right]. \quad (59)$$

Given the restriction  $\sigma < 1$ , this is positive when condition (12) is satisfied.

Differentiation of the equilibrium condition (10) with respect to  $\beta$  immediately yields that the left side rises in  $\beta$  when  $\beta \geq \beta_0$ , as defined in the text.

## 9 Appendix 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 1995-2005. Sources: EU KLEMS, 2012 release; 2019 release, IFR (2017).

Robot density in Japan, annual observations for 2006-2016. The total number of annual hours worked by industrial groups is available up to 2015. We impute the industry-level hours worked for the year 2016 using the average annual change of an industry's hours worked during the years 2006-2015. Sources: EU KLEMS, 2019 release, IFR (2017).

**Table 1. Manufacturing trade flows, 2014**

Country	Manufacturing %GDP	Exports %Manufacturing	Imports %Manufacturing
Austria	27.7	64.4	45.0
Belgium	25.5	76.3	60.2
Czechia	39.0	68.6	44.3
Denmark	19.5	63.7	41.2
Finland	27.3	52.3	35.5
France	19.3	46.7	39.2
Germany	33.0	55.6	32.4
Italy	28.8	40.8	26.5
Nether	22.8	66.6	58.1
Spain	27.2	37.9	33.7
Sweden	23.3	57.0	30.1
UK	15.1	37.4	39.9
USA	18.0	16.9	19.6

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**Sources**

Manufacturing output (gross) as percent of GDP, KLEMS 2019 release

Exports of domestically produced manufacturing goods, gross, Input-Output tables, WIOD database, November 2016 release

Imports of manufacturing goods, including intermediate goods and final consumption goods, Input-Output tables, WIOD database, November 2016 release.

**Table 2. Skills in manufacturing industries**

Country	Innovation Index scale 1-7	High Skill (percent)	Low Skill (percent)
Austria	4.7	17.5	16.8
Belgium	5.0	26.4	26.7
Czechia	4.2	9.1	6.8
Denmark	5.0	20.3	27.7
Finland	5.5	31.4	16.3
France	4.8	26.4	24.2
Germany	5.3	23.4	15.4
Italy	3.8	8.0	45.4
Netherlands	5.0	21.4	33.3
Spain	3.9	31.4	46.1
Sweden	5.4	19.1	17.5
UK	5.0	21.9	31.8
Correlations, all		0.431	-0.541
Correlations, excluding 2 outliers		0.829	-0.849

**Notes**

For the construction of the innovation index see text.

The columns headed high skill and low skill show the percentages of high skill and low skill workers employed in manufacturing industries, as defined by EU KLEMS 2019 release. The remainder percentage is that for medium skill workers.

The skill percentage numbers are mean values of all positive entries in the sample. Comparable percentages for the United States are not published.

The correlations show the correlation of each skill with the innovation index. The first row includes all the skill entries and the second drops two outliers, low skill for Czechia and high skill for Spain.

**Table 3. Country means of key variables**

Country	Innovation	Annual	Robot density	
	Index scale 1-7	Hours (millions)	manufacturing	Non-manuf.
Italy	3.79	8,713	10.91	0.04
Spain	3.92	5,421	9.21	0.10
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	0.10
Germany	5.28	10,115	14.30	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 4. Industry means of key variables**

Industry	Annual hours (millions)	Robot density
<i>Manufacturing</i>		
Electronics	488	4.91
Food and beverages	695	2.28
Metal	768	5.9
Plastics and chemical	792	5.77
Textiles	215	0.32
Transport Equipment	523	32.65
Wood and paper	349	1.3
<i>Non-manufacturing</i>		
Agriculture	1,045	0.03
Utilities	293	0.04
Mining and quarrying	66	0.26

**Notes**

Annual hours are 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 5. Results for manufacturing industries**

	Dependent variable in all regressions: log hours by country, industry and year, $\ln(H_{ict})$			
	(1) OLS	(2) OLS	(3) IV	(4) IV
$\ln(R_{ict}/H_{ict}) * I_1$	0.152 (0.018)	-0.956 (0.147)	0.248 (0.029)	-1.020 (0.249)
$\ln(R_{ict}/H_{ict}) * I_2$	-0.005 (0.008)	-0.194 (0.051)	0.026 (0.010)	-0.240 (0.058)
$\ln(R_{ict}/H_{ict}) * I_3$	0.052 (0.008)	-0.274 (0.049)	0.137 (0.014)	-0.275 (0.070)
$\ln(R_{ict}/H_{ict}) * I_1 * V_{ct}$		0.218 (0.029)		0.247 (0.047)
$\ln(R_{ict}/H_{ict}) * I_2 * V_{ct}$		0.038 (0.01)		0.054 (0.012)
$\ln(R_{ict}/H_{ict}) * I_3 * V_{ct}$		0.068 (0.01)		0.087 (0.015)
$\ln(K_{ict})$	0.651 (0.013)	0.634 (0.012)	0.593 (0.017)	0.560 (0.018)
$\ln(W_{ict}/H_{ict})$	-0.391 (0.043)	-0.332 (0.042)	-0.554 (0.057)	-0.467 (0.055)
country dummies	yes	yes	yes	yes
time dummies	yes	yes	yes	yes
industry dummies	no	no	no	no
Number of obs.	977	977	977	977
F(27, 949)	1290		1151.48	
F(30, 946)		1265.26		1089.68
Cragg-Donald Wald F			161.7	64.69

**Notes**

Subscript 1 denotes electronics, 2 transport equipment, and 3 low-tech industries. The instrument used is robot density in South Korea over the period of the sample. Robust standard errors in parentheses

**Table 6. Estimates of the net effect of robot density on hours of work, by country and manufacturing sectors**

Country	Electronics	Transport equipment	Low-tech industries	Country	Electronics	Transport equipment	Low-tech industries
Italy	-0.131 (0.040)	-0.049 (0.013)	-0.018 (0.013)	Denmark	0.129 (0.017)	-0.004 (0.008)	0.062 (0.008)
Spain	-0.104 (0.037)	-0.044 (0.012)	-0.010 (0.012)	UK	0.141 (0.017)	-0.002 (0.008)	0.066 (0.008)
Czechia	-0.034 (0.029)	-0.032 (0.010)	0.012 (0.010)	Germany	0.193 (0.018)	0.008 (0.009)	0.082 (0.009)
Austria	0.073 (0.019)	-0.013 (0.008)	0.045 (0.008)	Sweden	0.210 (0.019)	0.011 (0.009)	0.088 (0.009)
France	0.091 (0.018)	-0.010 (0.008)	0.051 (0.008)	Finland	0.238 (0.021)	0.015 (0.010)	0.096 (0.010)
Belgium	0.122 (0.017)	-0.005 (0.008)	0.060 (0.008)	USA	0.240 (0.021)	0.016 (0.010)	0.097 (0.010)
Netherlands	0.128 (0.017)	-0.004 (0.008)	0.062 (0.008)				

**Notes**

The table shows the net effect of the OLS estimated coefficients ( $\beta_1 + \beta_2 V_c$ ), where  $V_c$  is the sample mean of the innovation index for each country. Countries are listed in terms of increasing innovation index. Robust standard errors of the net effect are in parentheses

**Table 7. Impact of robot density on hours change, 2011-13 to 2014-16**

	Italy			Germany			USA		
	electronics	transport eq.	low-tech	electronics	transport eq.	low-tech	electronics	transport eq.	low-tech
mean hours 2011-13 (millions)	473.6	396.1	897.6	1206.7	1338.7	1108.9	2868.4	3001.5	20129.8
detrended change 2011-13 to 2014-16	-31.5	4.9	13.6	31.3	17.5	18.1	31.3	40.3	937.8
change attributed to robot density	-10.9	4.3	-2.6*	10.7	0.1*	9.6	327.6	14.3*	858.3

**Notes**

Detrending was done by including a time trend for hours in the regression and interacted with each industry separately

A \* indicates not significantly different from zero.

Robot density increased in all entries between the two periods except for Italy's transport equipment industry

**Table 8. Alternative specifications for manufacturing industries**

	Dependent variable in all regressions: log hours by country, industry and year, $\ln H_{ict}$			
	Industry dummies	Inter-actions	Inter-actions	2-way clustering
$\ln(R_{ict}/H_{ict}) * I_1$	-1.143	-0.984	-1.177	-0.956
	0.133	0.160	0.140	0.152
$\ln(R_{ict}/H_{ict}) * I_2$	-0.213	-0.207	-0.214	-0.194
	0.047	0.055	0.049	0.052
$\ln(R_{ict}/H_{ict}) * I_3$	-0.364	-0.282	-0.370	-0.274
	0.044	0.054	0.046	0.111
$\ln(R_{ict}/H_{ict}) * I_1 * V_{ct}$	0.240	0.224	0.246	0.218
	0.026	0.031	0.027	0.030
$\ln(R_{ict}/H_{ict}) * I_2 * V_{ct}$	0.032	0.041	0.031	0.038
	0.010	0.011	0.010	0.010
$\ln(R_{ict}/H_{ict}) * I_3 * V_{ct}$	0.071	0.070	0.071	0.068
	0.009	0.011	0.009	0.020
$\ln(K_{ict})$	0.638	0.631	0.635	0.634
	0.016	0.013	0.017	0.047
$\ln(W_{ict}/H_{ict})$	-0.278	-0.338	-0.281	-0.332
	0.044	0.047	0.047	0.100
country dummies	yes	no	yes	yes
time dummies	yes	no	no	yes
industry dummies	yes	no	no	no
Country*year	no	yes	no	no
Industry*year	no	no	yes	no

**Notes**

Subscript 1 denotes electronics, 2 transport equipment, and 3 low-tech industries. All estimates are with OLS (with robust standard errors) for 977 observations. The two-way clustering in the last column is for 77 industry-year clusters.

**Table 9. Net coefficient estimates with alternative innovation indices**

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Industry	Index	Italy	US/Sweden
Electronics	WEF	-0.131	0.240
	GII	0.011	0.226
	EU	-0.150	0.341
Transport Equipment	WEF	-0.049	0.016
	GII	-0.025	0.012
	EU	-0.042	0.016
Non-tech	WEF	-0.018	0.097
	GII	0.029	0.071
	EU	-0.011	0.127

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**Notes**

The table shows the net coefficient estimated for the impact of robot density on hours of work. See Table 6 for details. The three innovation indices are the World Economic Forum (WEF, as in Table 6), Global Innovation Index (GII) and the European Union Summary Index (EU)

**Table 10. Results for manufacturing and non-manufacturing industries**

	Dependent variable in all regressions: log hours by country, industry and year, $\ln(H_{ict})$	
	(1) OLS	(2) OLS
$\ln(R_{ict}/H_{ict}) * I_1$	0.251 (0.018)	-0.595 (0.181)
$\ln(R_{ict}/H_{ict}) * I_2$	0.041 (0.008)	-0.061 (0.061)
$\ln(R_{ict}/H_{ict}) * I_3$	0.083 (0.008)	-0.075 (0.059)
$\ln(R_{ict}/H_{ict}) * I_4$	-0.065 (0.011)	-0.065 (0.011)
$\ln(R_{ict}/H_{ict}) * I_1 * V_{ct}$		0.167 (0.036)
$\ln(R_{ict}/H_{ict}) * I_2 * V_{ct}$		0.021 (0.013)
$\ln(R_{ict}/H_{ict}) * I_3 * V_{ct}$		0.033 (0.012)
country dummies	yes	yes
time dummies	yes	yes
industry dummies	no	no
Number of obs.	1285	1285
F(29, 1225)	1156.12	
F(30, 946)		1068.49

**Notes**

Subscript 1 denotes electronics, 2 transport equipment, 3 low-tech industries, and 4 the non-manufacturing sectors (agriculture, mining and quarrying and utilities). Robust standard errors in parentheses

**Table 11. 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
$\ln(R_{ict}/H_{ict}) * I_1$	-0.257 (0.047)	-0.245 (0.045)	-0.213 (0.036)	-0.188 (0.036)	-0.132 (0.038)	0.081 (0.052)
$\ln(R_{ict}/H_{ict}) * I_2$	-0.777 (0.135)	-0.447 (0.147)	-0.739 (0.106)	-0.681 (0.109)	-0.386 (0.112)	-0.310 (0.130)
$\ln(R_{ict}/H_{ict}) * I_3$	-0.123 (0.047)	-0.109 (0.046)	-0.135 (0.036)	-0.167 (0.037)	-0.135 (0.045)	-0.119 (0.063)
$\ln(R_{ict}/H_{ct}) * I_1 * V_{ct}$	0.062 (0.009)	0.055 (0.008)	0.057 (0.007)	0.049 (0.007)	0.046 (0.009)	-0.005 (0.010)
$\ln(R_{ict}/H_{ict}) * I_2 * V_{ct}$	0.175 (0.025)	0.107 (0.026)	0.175 (0.021)	0.161 (0.021)	0.129 (0.027)	0.089 (0.025)
$\ln(R_{ict}/H_{ict}) * I_3 * V_{ct}$	0.023 (0.009)	0.019 (0.008)	0.027 (0.008)	0.033 (0.007)	0.032 (0.011)	0.023 (0.013)
No. obs.	977	977	977	977	977	977
F (30,946)	1251.23	1223.68	1290.97	1274.49	1210.23	1178.1

**Notes**

The coefficients in this table were estimated with OLS regressions like the one in column (2) of Table 5, with each of the six components of the *National Innovation Index* replacing the aggregate index in turn. Robust standard errors in parentheses.



**Table 12. Results for manufacturing industries**

	Dependent variable in all regressions: log hours by country, industry and year, $\ln(H_{ict})$			
	(1) OLS	(2) OLS	(3) IV	(4) IV
$\ln(R_{ict}) * I_1$	0.113 (0.0074)	-0.117 (0.037)	0.248 (0.029)	-0.231 (0.049)
$\ln(R_{ict}) * I_2$	0.068 (0.0058)	-0.077 (0.027)	0.026 (0.010)	-0.342 (0.067)
$\ln(R_{ict}) * I_3$	0.099 (0.0069)	-0.015 (0.028)	0.137 (0.014)	-0.226 (0.063)
$\ln(R_{ict}) * I_1 * V_{ct}$		0.046 (0.007)		0.065 (0.010)
$\ln(R_{ict}) * I_2 * V_{ct}$		0.029 (0.005)		0.098 (0.013)
$\ln(R_{ict}) * I_3 * V_{ct}$		0.023 (0.006)		0.073 (0.013)
$\ln(K_{ict})$	0.552 (0.015)	0.537 (0.015)	0.593 (0.017)	0.560 (0.018)
$\ln(W_{ict}/H_{ict})$	-0.439 (0.044)	-0.393 (0.044)	-0.554 (0.057)	-0.467 (0.055)
country dummies	yes	yes	Yes	Yes
time dummies	yes	yes	Yes	Yes
industry dummies	no	no	No	No
Number of obs.	977	977	977	977
F(27, 949)	1463.22		1151.48	
F(30, 946)		1381.22		1089.68
Cragg-Donald Wald F			161.66	64.69

**Notes**

Subscript 1 denotes electronics, 2 transport equipment, and 3 low-tech industries. The instrument used is robot density in South Korea over the period of the sample. Robust standard errors in parentheses