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

Chrystalla Kapetaniou
University of Southampton, Great Britain

Christopher A Pissarides*
London School of Economics, Great Britain
and University of Cyprus, Cyprus

running head: Robots and Industrial Employment

Abstract

In a model with robots, automatable and non-automatable production, we study robot-labour substitutions and show how they are influenced by a country's "innovation system". Substitution depends on demand and production elasticities, the country's innovation capabilities and openness. 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 might complement them. Innovation capabilities play a bigger role in the high-tech electronics sector than in other manufacturing and play a limited role in non-manufacturing.

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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 analyze the impact of the introduction of robots on the allocation of hours of work, in an economy which uses both automatable and non-automatable production technologies; namely production technologies with high and low robot-labour substitution elasticities.

In a theory section we develop a model of an open economy with a robot-using sector, which produces its output with a nested production function with two labour inputs, one a substitute and the other a complement to robots. We show that equilibrium allocations depend on several parameters, with the elasticities of substitution between production inputs and the elasticity of final demand playing a key role. A fall in the price of robots relative to the price of labour could lead to either an increase or a decrease in overall hours of work in the robot-using sector of the economy, depending on the values taken by these parameters.

We then switch to multi-country empirical work and discuss the institutions that are summarized in the country's "national innovation system." A national innovation system is defined as a network of institutions, including universities, industrial research units and other technical and scientific establishments, whose activities and interactions affect the technological development of an economy. It summarizes the "innovation capabilities" of a country, and it includes the areas of the economy that affect searching, exploring and learning, which are all critical activities for the acquisition and generation of knowledge.[1]

Robots are capital goods embodying a new "automation" technology that might displace or complement labour, measured by hours of work. In our empirical work we show that as in the pioneering work of North (1990), or the more recent work by Acemoglu and Robinson (2012), the impact of robots on hours depends on the institutional structure of the country, in this case its innovation system. In estimates with data from thirteen industrial countries over the period 2006-2016, we find that in contrast to earlier work, taking into account the innovation system of a country gives precise results about the impact of robots on hours of work. Countries that rank low in their national

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

innovation system substitute robots for human labour more than countries that rank higher, which might increase hours when robots are introduced. Access to international markets is an important channel through which these effects take place. Countries with better innovation systems are better able to use the robotics technology to increase their productivity relative to other countries. This improves their trade balance and so they increase domestic production to meet this additional demand.

Our model 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 relative price, which is widely documented and which we take as exogenous.[2] An innovation of our CES production function in manufacturing is that hours are of two types. One type has high elasticity of substitution with robots, which we call automatable, and intuitively associate with assembling goods, and a second one has low elasticity of substitution, which we associate with management, research, sales and robot maintenance. Our CES structure is nested, such that the automatable part produces intermediate goods which are subsequently combined with the second type of labour into final output. The economy is closed by a second sector that has a simple linear technology in labour only. Our nested production structure could be given a simplified task-based interpretation, with two types of tasks, the automatable one that is characterized by a high elasticity of substitution between capital and labour, and the non-automatable one that is characterized by a low elasticity of substitution.

In the derivation of the impact of a lower robot price on hours, we find that production and demand 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 overall price elasticity of the final demand for output, which is made up of the domestic elasticity and the elasticity of demand for imports and exports.

The link between the innovation capabilities of a country and these findings is provided by a key assumption, which was motivated by the arguments elaborated in the literature on national innovation systems.[3] This is that countries with better innovation capabilities invent new production meth-

[2]See for example, International Federation of Robotics (IFR 2017) and Graetz and 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.

[3]See the references in footnote 1

ods, or make better use of the existing automation technologies, to achieve a more productive combination of robots and labour. In the nested production function this is represented by a higher TFP of the automatable part of production in countries with better innovation systems, which is the only part of production that employs robots.

To give more intuition to this assumption we can think of robots as generic blueprints that are brought into production, and local expertise is adapting them to use in the automatable part of production. A country with better innovation capabilities, in the form of better research institutions and scientific personnel, is able to develop a more productive combination of robots and hours of work out of the blueprints than one with weaker innovation capabilities.

With this assumption, the main result of our theoretical model is that there are two channels through which the innovation system influences the net robot-labour substitutions. The first channel holds in the closed as well as the open economy. It is that if the domestic demand elasticity exceeds the low elasticity of substitution between the intermediate output of the automatable part of production and the labour employed in the non-automatable part, 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 complementarity between hours in the non-automatable part and the intermediate output of the automatable part of production. The innovation in this result is that unlike earlier derivations, for a (possible) positive impact on hours of work, the final demand elasticity does not have to exceed the high elasticity of substitution between robots and hours in the automatable part of production, but the low one in the non-automatable part.[4] We show that in countries with a more advanced national innovation system the positive (complementary) effect on hours is relatively stronger than the negative (substitutable) effect than it is in countries with weaker systems. An intuition for this result is that because of the higher productivity of the automatable part of production in countries with a stronger innovation system, a given substitution of robots for labour in the automatable part of production produces more intermediate output in the country with the stronger system, and so increases the demand for complementary labour by more.

[4]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 Ngai and Pissarides (2007), Acemoglu and Guerrieri (2008) and Herrendorf, Rogerson and Valentinyi (2014) for a survey.

The second channel through which the innovation system influences the substitutions is international trade. Because of the higher productivity of the automatable part of production, countries with a more advanced innovation system have a comparative advantage in international trade. When robots are introduced their productivity rises by relatively more than the productivity of countries with weaker systems, lowering the relative international price of their manufacturing goods and so raising the international demand for their outputs. Domestic firms increase the number of hours of work to meet this demand.[5]

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, seven manufacturing sectors and three non-manufacturing sectors.[6] 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 hours of work measured in millions) 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, Carbonero, Ernst and 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

[5]Matsuyama (2009) has derived the related result for a biased rise in sectoral productivity. An increase in comparative advantage from biased technological progress has a positive impact on employment in the sectors that experience the faster productivity growth, which acts against the negative closed-economy effect when the domestic demand elasticity is low.

[6]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. The seven manufacturing sectors are electronics and electrical goods, food and beverages, metals, plastics and chemicals, textiles, transport equipment, and wood and paper, and the three non-manufacturing sectors are agriculture, utilities and mining and quarrying.

average have poorer innovation systems than industrial countries, so they are more likely to use robots to substitute labour without complementary job creation.[7]

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. To compute our innovation index we extract from the World Economic Forum's *Global Competitiveness Report* (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 the scores for six indicators: the availability of scientists and engineers, collaborations between universities and industry in R&D, government procurement of technology products, quality of scientific research institutions, company spending on R&D and capacity for innovation. The individual scores are compiled by the World Economic Forum from surveys of senior company executives.

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 much less so 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, there are stronger substitutions between labour and robots, but the national innovation system still plays an important role; in countries with a strong system the estimates are either not significantly different from zero or they are weak positive. We also tested substitutions in three production sectors that do not belong to manufacturing, agriculture, mining and utilities, which are very small users of robots, and found that robots substitute hours regardless of the innovation system of the country.

The rest of the paper is organized as follows. Section 2 describes our model of two sectors, one that uses robots and one that does not. Section 3 defines the innovation system of a country and discusses the channels through which it influences the equilibrium of the economy and the robot-labour

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

substitutions. In section 4 we discuss our data and in section 5 we show our estimation results. In an Online Appendix we report further tests of our empirical specification with a number of extensions and robustness tests. The main results discussed in the Online Appendix are summarized in section 6, and the overall results of the paper in section 7.

2 A two-sector model with robots and labour

The objective of this section is to solve an equilibrium model that can be used to derive the connections between robots and hours of work. The 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 mostly modelled the adoption of robots as the profit-maximizing choice between humans and robots in the performance of particular tasks.[8] Our approach can be interpreted along similar lines to the task-based approach, with labour performing two types of tasks. One type has a high elasticity of substitution with labour, and the other a low elasticity of substitution. The classification of tasks into two types, rather than a continuum, enables us to write the technology facing the robot-using firm as a nested CES production function, and use conventional techniques to get the equilibrium solution.

We define the production function over hours of work and assume that robots are the only capital good.[9] Our formulation is consistent with two well-known observations. First, a company that employs workers in activities that can be automated through the adoption of robots, also employs workers in activities that are complementary to the output of robots. The allocation of hours of work to these two types of activities is a matter decided by profit-maximizing criteria and parameter values.[10] Second, in an economy-wide model, the introduction of robots is not uniform across sectors, and this

[8]On the former, see the pioneering work of Frey and Osborne (2017) and the many studies that followed, e.g., McKinsey Global Institute (2017), Nedelkoska, and Quintini (2018) and Josten and Lordan (2020). On empirical modelling see Acemoglu and Restrepo (2020) and Graetz and Michaels (2018). A notable early exception using more conventional techniques to study the substitutions between labour and capital is Zeira (1998).

[9]For intuition within the task-based approach, we can think of an hour of work as the time needed to complete a task. The rest of the analysis would be virtually unaltered. Capital other than robots could be introduced in a separate production nest but it would complicate the analysis with no additional insights for the correlations between robots and hours of work.

[10]See Lin (2011) and Acemoglu and Restrepo (2019). This was also noted in more applied research, e.g., by the McKinsey Global Institute (2017), in reference to changes in sectors such as banking.

causes employment reallocations across sectors, which may have an impact on robot-labour substitutions through price and wage affects.

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 engaged in tasks that can be automated, such as those on assembly lines. 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 in this part of production is low, as the people working here are engaged in improving car quality, improving the organization of production, and when the output is done, take the cars to the market.

Our argument is that as robots displace workers in some parts of manufacturing production, new jobs are created in manufacturing itself, but other jobs can also be created in the service sectors of the economy to take any workers leaving manufacturing.

We consider a model of an open economy with two sectors in full employment equilibrium. Sector 1 produces a consumption good, which is tradable, 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 tradable. Sector 2 is modelled as a labour intensive sector with linear technology, which simplifies the equilibrium analysis. 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 at a fixed and exogenous price ρ, 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.[11]

A firm in the robot-using sector has a two-part nested production structure. One part produces some intermediate output F by employing both robots and labour, with some finite but large elasticity of substitution. We call this the automatable part of production. A second higher-level part of the overall production structure employs labour that 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 elasticity of substitution between the automatable output F and the labour employed in the non-automatable part of production is positive

[11] See International Federation of Robotics (2017) and Graetz and Michaels (2018).

but low.

The automatable part has production function,

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

where H_{1R} are the hours supplied by human labour, R are the robots employed in the sector, V is a productivity parameter and $\alpha \in [0,1]$, $s > 0$ are parameters. F is intermediate output.

Parallel to this production activity, firms in the robot-using sector employ labour in the non-automatable part of production, with production function,

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

Here Y_1 is the output of sector 1, H_{1N} are the hours of work employed in the non-automatable part of production, $\beta \in [0,1]$ is a parameter and $\sigma > 0$ is the elasticity of substitution between the automatable part of production and the non-automatable one. The parameter A_1 is another productivity parameter.

On the basis of our earlier discussion, we assume that $\sigma < 1$ and $s > \sigma$; i.e., that the intermediate output produced in the automatable part of production is complementary to the labour employed in the non-automatable part, and that robots are a strong substitute for labour employed in the automatable part of production. (We argue later that $s > 1$, although our results will go through as long as $s > \sigma$.) The manufacturing firm 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,

$$Y_2 = A_2 H_2, \tag{3}$$

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,

$$\max_{c_1,c_1^*,c_2} U(c) = \ln\left[\omega\tilde{c}_1^{(\varepsilon-1)/\varepsilon} + (1-\omega)c_2^{(\varepsilon-1)/\varepsilon}\right]^{\varepsilon/(\varepsilon-1)} \tag{4}$$

$$\tilde{c}_1 = \left[\psi c_1^{(\eta-1)/\eta} + (1-\psi)c_1^{*(\eta-1)/\eta}\right]^{\eta/(\eta-1)} \tag{5}$$

$$\sum_{i=1}^{2} p_i c_i + p_1^* c_1^* \leq Y, \tag{6}$$

where c_1 and c_2 are the consumption levels of the domestic goods 1 and 2, c_1^* is the consumption of imports and Y is aggregate income. We assume $0 < \omega < 1$ and $0 < \psi \leq 1$, allowing for the case of the closed economy when $\psi = 1$. The elasticities ε and η are both positive, with $\eta \geq \varepsilon$ (see below for more discussion). p_1 and p_2 are domestic prices and p_1^* is the exogenous price of imports.

Although we do not model explicitly the foreign sector to derive an equilibrium value for p_1^* or for the demand for exports, later in this section we make some assumptions that enable us to treat foreign demands and prices symmetrically to those of the domestic economy. Here we complete the description of the model by writing c_1^{**} for exports.

Labour markets clear subject to the resource constraint,

$$H_1 + H_2 \leq 1, \text{ where} \tag{7}$$

$$H_1 = H_{1R} + H_{1N}. \tag{8}$$

Output markets clear according to

$$c_1 + c_1^{**} \leq Y_1, \qquad c_2 \leq Y_2 \tag{9}$$

$$Y = p_1 Y_1 + p_2 Y_2. \tag{10}$$

Equation (9) says that domestic output is either consumed domestically or exported, and equation (10) says that aggregate income is equal to the value of domestic output.

Definition. *Equilibrium is defined by an allocation for consumption goods that satisfies the consumer maximization problem (4)-(6), a labour and robot allocation that maximizes profit* $p_1Y_1 - (H_{1R} + H_{1N} - \rho R)W$ *subject to the resource constraint (7) and prices* p_1, p_2 *and* W *that satisfy the market clearing conditions (9)-(10), for given production functions (1)-(3), exogenous relative robot price* ρ, *demand for exports* c_1^{**} *and foreign price* p_1^*.

We state here the main results of the model for a given innovation system and terms of trade in two Propositions, and collect all derivations and proofs in the Appendix. Proposition 1 is proved by making use of the firm's marginal productivity conditions, so the consumption, import and export conditions are not used in the proofs.

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. The lower robot price is due to technological improvements in the robot-producing sector, which is not modelled here, so it is an example of a technological improvement in an intermediate goods sector (the robots) 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.

In order to derive results for the allocation of hours across the two sectors we need to bring in the demand side. The relative prices derived in the proof of Proposition 1 in the Appendix are given by:

$$\frac{p_1}{p_2} = \frac{A_2}{A_1 X^{1/(\sigma-1)}} \tag{11}$$

$$X \equiv V^{\sigma-1} q^{\sigma-1} (1-\beta)^{\sigma} + \beta^{\sigma} \tag{12}$$

$$q \equiv \left[\alpha^{s} + (1-\alpha)^{s} \rho^{1-s}\right]^{1/(s-1)}. \tag{13}$$

In order to give some intuition to these results, let Wp_F be the implicit price at which the firm producing Y_1 could buy the intermediate output F (e.g., if it was produced by someone else). Then from the definition of F in (1) and the optimal relative inputs derived in the Appendix, (24) and (25), we derive that $p_F = 1/Vq$. So q is proportional to the inverse of the cost of F to the firm. In parallel to this interpretation, $X^{1/(\sigma-1)}$ is proportional to the inverse of the cost of producing the final output, which explains the reason for the price ratio in (11). Since $q'(\rho) < 0$, and α and s are fixed technology parameters, when convenient we could use q in place of ρ, with a rise in q signifying a fall in robot price and consequently of the implicit cost of F to the firm.

The MRS conditions derived from the consumption model in (4)-(6), yield the demand-side solution for relative prices,

$$\frac{p_1}{p_2} = \frac{\omega}{1-\omega} \psi^{\eta/\varepsilon} \left(\frac{\tilde{p}_1}{p_1}\right)^{(\eta-\varepsilon)/\varepsilon} \left(\frac{c_1}{c_2}\right)^{-1/\varepsilon} \tag{14}$$

$$\tilde{p}_1 = \left[\psi^{\eta} p_1^{1-\eta} + (1-\psi)^{\eta} p_1^{*1-\eta}\right]^{1/(1-\eta)}. \tag{15}$$

Equating the two relative price expressions, (11) and (14), and making use of (9) and the production functions (see the Appendix for detailed derivations), we obtain the relative employment levels,

$$\begin{aligned} \frac{H_1}{H_2} = {} & \left(\frac{\omega}{1-\omega}\right)^{\varepsilon} \left(\frac{A_1}{A_2}\right)^{\varepsilon-1} \left[V^{\sigma-1} q^{\sigma-s} \alpha^{s} (1-\beta)^{\sigma} + \beta^{\sigma}\right] X^{\frac{\varepsilon-\sigma}{\sigma-1}} \\ & \psi^{\eta} \left(\frac{\tilde{p}_1}{p_1}\right)^{\eta-\varepsilon} \left(1 - \frac{c_1^{**}}{Y_1}\right)^{-1}. \end{aligned} \tag{16}$$

The full solution for the allocation of hours is given by (16) and the resource constraint (7).

The top line of (16) gives the impact of the substitutions between the automatable and non-automatable parts of production on the allocation of hours. The same expression holds both in the open and the closed economy. For $\beta = 0$ production is given by the automatable part $A_1 F$ only, and the top line of (16) becomes $\left(\frac{\omega}{1-\omega}\right)^{\varepsilon}\left(\frac{A_1 V}{A_2}\right)^{\varepsilon-1} q^{\varepsilon-s}\alpha^{s}$.

The second line of (16) shows the contribution of imports and exports to the allocation of hours. The key endogenous variable here that influences imports is the ratio of foreign to domestic manufacturing prices, p_1^*/p_1. From (15) and the (empirical) assumption $\eta > \varepsilon$, a rise in p_1^*/p_1 raises H_1/H_2 : the higher relative price makes imports more expensive and so consumption switches to home manufacturing.

We model exports by treating them as imports of a similar foreign country. Higher p_1^*/p_1 makes this country's exports cheaper internationally, raises c_1^{**}/Y_1, and so from the export contribution $(1 - c_1^{**}/Y_1)^{-1}$in (16) it raises H_1/H_2. Let the elasticity by which H_1/H_2 rise be $\xi > 0$ (which may or may not be constant). The contribution of international trade to the allocation of hours is now simple to summarize, as it depends on the single ratio p_1^*/p_1 according to the three elasticities η, ε and ξ, the first being the elasticity of substitution between imported and domestic manufacturing goods, the second the elasticity of substitution between domestic manufacturing and service goods and the third a price elasticity that summarizes the contribution of exports to relative hours.

For p_1^*/p_1 we assume a function that reflects the result found in (11) and treats domestic and foreign prices symmetrically. Since both traded goods are produced by the domestic and foreign sector 1, relative prices are equal to the inverse of productivities in this sector:

$$\frac{p_1^*}{p_1} = \frac{A_1 X^{1/(\sigma-1)}}{A_1^* X^{*1/(\sigma-1)}}. \tag{17}$$

This ratio is equal to 1 unless there are country-specific parameters in the respective production functions. We discuss this issue in the next section.

In the closed economy $\psi = 1$ and $c_1^{**} = 0$, so the last two terms of (16) are both unity and the solution for H_1 contains only parameters. We can show

Proposition 2 *In the closed economy lower robot price raises hours of work in the robot-using sector when the ratio $(\varepsilon - \sigma)/(\sigma - s)$ exceeds a strictly positive constant $K \leq 1$, which is monotonically decreasing in β. The maximum* *value $K = 1$ is obtained for $\beta = 0$, at which value the standard condition for a positive impact on hours, $\varepsilon > s$, obtains.*

The result is given by the differentiation of the first part of expression (16) with respect to robot price, given the maintained assumption $s > \sigma$. The net impact of a fall in robot price on hours in sector 1 is positive when,

$$\frac{\varepsilon - \sigma}{s - \sigma} \geq \frac{V^{\sigma-1}(1-\beta)^{\sigma} q^{\sigma-1} + \beta^{\sigma}}{V^{\sigma-1}(1-\beta)^{\sigma} q^{\sigma-1} + \beta^{\sigma} \alpha^{-s} q^{s-1}} \equiv K, \tag{18}$$

with q defined in (13). Given the definition of q, $\alpha^{-s} q^{s-1} \geq 1$ and so $K \leq 1$ and $\partial K / \partial \beta \leq 0$. For $\beta = 0$ it follows trivially that $K = 1$.

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, cited in footnote 4). In this case, the inequality in (18) becomes $\varepsilon \geq s$.

The dependence of K on β brings out the significance of the nested production structure and the second type of labour input for our results. The relatively larger the second type of labour is, as shown by a higher β, the lower is the constant K, and the more likely is (18) to hold. To give intuition to what is going on with the two-tier production structure, suppose there are two types of firms, one producing the intermediate output F and the other buying F and combining it with labour to produce final output. When the cost of producing F falls, we know from standard results that employment in the automatable part will increase if the elasticity of the demand for F exceeds the elasticity of substitution between labour and capital (robots) in the production of F. These are, respectively, σ and s, as the output of the firm producing F is bought by the firm with elasticity of substitution σ. As $\sigma < s$, the fall in the price of robots always reduces the demand for hours in the automatable part of production.

For the firm producing final output, the fall in the price of F yields an increase in the demand for hours if $\varepsilon > \sigma$, given that the demand elasticity for final output is ε. If this is satisfied, demand for hours in the non-automatable part of production increases, working against the fall in hours in the automatable part. Clearly, $\varepsilon \leq \sigma$ is a sufficient condition for a fall in overall hours when robot price falls.

Recall that this holds only in the closed economy. In the open economy import and export effects introduce additional influences on hours allocations, provided the fall in the relative price of robots changes the terms of trade p_1^*/p_1. In symmetric equilibrium, when all countries have identical parameters, the terms of trade do not change and there are no open economy effects. We argue in the next section that different innovation systems across countries produce asymmetries, and derive their impact on hours.

3 The role of the national innovation system

The national innovation system of a country is a multi-dimensional concept that depends on several properties of the research environment of the country.[12] Our motivation for its use is as a way of measuring the country's *innovation capabilities.* It depends on the quality of the country's human capital (measured in a variety of ways by different indices and in the case of our index by the availability of scientists and engineers), on collaborations between companies and universities, on the facilities offered by governments, and generally on the ease with which companies can engage in R&D. Other measures of innovation systems, discussed in the Online Appendix, use related criteria to construct their index, but the numbers they come up with (at least for the countries in our sample) are highly correlated with our own. Overall, a higher index of innovation capabilities indicates a country with better facilities for research, development and applications of new technologies. We make the key assumption:

Assumption. *Countries with a better innovation system (equivalently, stronger innovation capabilities) have higher-valued productivity parameter* V.

Assuming that A_1, or A_2, are also higher in a country with a better innovation system might be a natural assumption to make but qualitatively they have no influence on our results, or any new implications about the role of the national innovation system on the relation between robot price and hours of work. The motivation for focusing on V is that it is an index of productivity in the sub-sector that uses the automation technology. A country with better innovation capabilities is better at developing and adapting the automation blueprints of the new technologies to the particular circumstances of its business environment. In our model, any impact of the innovation system on the relative productivities of the two domestic sectors, or of the country's international productivity comparisons, acts via V. Given the importance of V in influencing the role of innovation capabilities in our model, we can refer to it as the innovation capabilities index of the country.

Our focus in the empirical work is to estimate the elasticity by which a fall in robot price (equivalently, a rise in robot density, given the result in Proposition 1) changes hours of work in the robot using sector of the economy, and how this elasticity depends on the country's innovation capabilities. We study the influence of the productivity parameter V (our measure of innovation capabilities) on this elasticity in the closed and open economies with reference to equation (16), which gives the equilibrium allocation of hours.

[12] See the references in footnote 1 for more discussion.

3.1 The closed economy

From (18) and Proposition 2 it is easy to show,

Proposition 3 *For $\sigma < 1$, the constant K in Proposition 2 is lower in countries with higher innovation index V, so a fall in robot price is more likely to deliver a rise in overall hours of work in the robot-using sector, provided $\varepsilon > \sigma$. For $\sigma = 1$ the innovation system has no impact on the response of hours to the fall in robot price, and for $\sigma > 1$ hours fall by more in countries with better innovation systems.*

Differentiation of (18) with respect to V immediately demonstrates the validity of this Proposition, given that $\alpha^{-s}q^{s-1} \geq 1$.[13]

3.2 The open economy

The assumed differences in the productivity parameter V across countries give rise to differences in country responses to the international fall in robot price, despite the assumed symmetry between countries in all other dimensions. Trade patterns will change, because of different responses of productivity and prices in countries with different innovation systems.

The channel through which the productivity parameters influence the robot-hours substitution with trade is the relative price p_1^*/p_1. As we noted earlier in this section, a higher p_1^*/p_1 reduces imports and raises exports, and so it raises the production of manufacturing goods in the home economy, with positive effects on hours of work.

The Appendix shows that the following Proposition holds,

Proposition 4 *Consider two countries that trade, the "foreign" one characterized by innovation capabilities V^* and the "domestic" one by $V \geq V^*$. For $\sigma \neq 1$, a fall in the price of robots raises p_1^*/p_1, and so increases hours in the traded sector. The reverse holds if $V \leq V^*$.*

The results of this proposition are driven by productivity: countries with a better innovation system are able to increase their manufacturing productivity by more than other countries when robot price falls, and so they become more competitive in international markets. The reason that their productivity increases by more is that any given rise in q, caused by a fall in robot price, has an amplified effect on the implicit cost of the intermediate output F, because V and q impact the cost multiplicatively. Refer to the discussion immediately following equations (11)-(13).

[13] In this expression the productivity parameters A_1 and A_2 are absent, which justifies our claim that they can be ignored when discussing the role of a country's innovation system.

3.3 Elasticities: what do we know?

We have identified three channels through which the innovation system influences the marginal impact of the introduction of more robots on hours of work: the substitution between automatable and non-automatable hours, which holds in both the closed and open economy, imports, and exports. Quantitatively, each one is driven by one or more elasticities. The substitution between hours in the automatable and non-automatable parts is driven by the difference $\varepsilon - \sigma$ relative to the difference $s - \sigma$. For this channel to have a large impact on hours requires a large ε compared with s. Imports are driven by the elasticity difference $\eta - \varepsilon$, and exports by ξ.[14]

In the survey of estimates examined by Ngai and Pissarides (2008), a plausible range for ε for the United States, in a two-sector model of services and manufacturing, was found to be between 0 to 0.3. Similar results were derived by Herrendorf et al. (2013) for value-added consumption bundles. These estimates are derived from consumer demand equations or spending shares, mainly for the United States, so they approximate the closed economy values. We were also able to find just one estimate for the elasticity s, from Cheng et al. (2021), who estimate substitution elasticities in the automatable part of production for Chinese industries, and find an s between 3 and 4.5, with a preferred point estimate of $s = 3.8$.

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 goods 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. Many electronic products are inputs into other industries, which will have a higher elasticity of demand as there are competing factors.

In the open economy elasticities are generally higher because traded manufacturing goods are close substitutes, e.g., German cars versus French cars. 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 manufacturing goods range from 30.6% of manufacturing output

[14] 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 elasticities ε and s, but not σ or the innovation system, which play a critical role here.

in Italy to 53.0% for the Czech Republic, and imports from 24.8% in Italy to 50.3% in Denmark. Their sum exceeds 90% of output in five of the thirteen countries in the sample.

Imbs and Mejean (2010) 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 biggest quantitative impact of the innovation environment originates in imports and exports, and the bigger the fraction of manufacturing output that is traded, the bigger this effect is likely to be. 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 0.42 as weight, the contribution to the overall manufacturing elasticity coming from imports is 0.73. This is substantially higher than the elasticity of substitution between manufacturing and services estimated for the United States. In addition, there is an impact from the high elasticity of demand for exports. We conclude that existing evidence on trade elasticities is consistent with a sufficiently large influence of the innovation system on the impact of robots on hours of work through this channel.

Our testing procedure for the differences in the impact of robots on hours in different countries is to estimate the elasticity of hours with respect to robot density (the ratio of robots in production to hours of work), and make this elasticity dependent on two other factors, the country's index of innovation capabilities and its openness to trade. On the basis of the theoretical discussion in the preceding section, we should expect a better innovation system to have a positive influence on the impact of robots on hours of work, whereas countries with more exposure to international trade should experience a bigger impact of robots on hours. But whether this impact is positive or negative depends on the country's innovation capabilities relative to those of its trading partners. As our countries are highly productive advanced industrial countries and trade also with less innovative countries not in our sample, we should expect the positive impact from international trade to dominate over any negative effects, at least for the countries with a high innovation index. However, this is an empirical issue that can only be resolved by the estimation.

4 The data

For our innovation index, we used the innovation capabilities pillar (no. 12) of the World Economic Forum's *Global Competitiveness Report*, which has been available in its current form since 2006.[15] 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 Schwab 2017, 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.[16] Table 2 gives the country sample means for the index and some other country variables.

Since we measure the innovation system by "innovation capabilities," human capital plays an important role in our analysis. Innovation activities, such as R&D, are conducted by highly trained employees. 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 system 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. We tested whether using a human capital index would give the same results as our innovation index but results were much poorer both statistically and in interpretation. Full results are given in the Online Appendix.[17]

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

[16] For patents the World Economic Forum takes the number of applications filed under the Patent Cooperation Treaty (PCT) and normalizes it to a scale of 1-7 to align it with the results of the Executive Opinion Survey. The way of counting patents, however, changed during the years of the sample and it was not possible to go back and adjust the earlier numbers on the basis of the new counting method. Partly because of this change, partly because the patent indicator is based on a different collection method from the other six, we 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.

[17] The human capital index that we used was the percentage of 25-64-year-olds with

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 in Table 2, 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 North America 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, Germany, Sweden, Finland and the United States, as the innovation leaders. The mean value of the index is 4.85, with France approximately in the middle, four other countries below it and the remaining eight above it.

We measure a country's openness to trade by the sum of manufacturing imports and (gross) manufacturing exports, divided by the country's total manufacturing output. Our source for all three are the Input-Output tables, WIOD database, November 2021 release. The sample means of openness for each country are given by the sum of the first two columns in Table 1.

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 (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 on the seven manufacturing sectors but we also include three non-manufacturing sectors in some of the tests for comparisons. 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.[18]

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

tertiary education over our sample, 2006 – 2016, compiled by the OECD. See Online Appendix, section 2.2.

[18] The three non-manufacturing sectors in Table 3 were the only ones with non-trivial robot usage in our data. Their robot density is very small compared with manufacturing, being about as small as 1% of robot density in the manufacturing sectors. Initially we also included construction in our sample, which uses some robots, 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 is 0.16% of the average number of manufacturing robots (one sixth of 1%). When included results were distorted because the large number of hours and small number of robots made it an outlier.

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).[19]

Our employment variable is hours of work in each sector and country. 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 2 and 3), with transport equipment being the biggest user of robotic technologies. This partly explains the big robot density values for Germany, France and Italy. But robot density is also high in Denmark and Finland, which are not big producers of transport equipment. Non-manufacturing sectors are very small users of robots when compared with manufacturing.

5 Empirical model: Elasticity estimates

5.1 Motivation for the estimated equation and expected signs

As we emphasized in section 3, our objective is to estimate the key elasticity that connects hours of work and robots, and how it is influenced by the country's innovation system; not to do a structural estimation of the model. The estimated elasticity is derived from (16), after H_2 is substituted out from the resource constraint $H_1 + H_2 = 1$, and robot price ρ (or its transformation in q), is replaced by robot density, making use of the robot density formula (28) of the Appendix. We have shown that a fall in ρ raises robot density, R/H_1; see Proposition 1.

The impact of robot price on hours of work and its dependence on the innovation system and openness were derived in several steps in Propositions

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

2, 3 and 4. As in previous work, the elasticity connecting hours and robot density cannot be signed *a priori*, but mixed quantitative estimates exist in the literature, as summarized in the Introduction. The predictions that can be tested by estimating the elasticity based on the results of our model are (1) a measure of the country's innovation system has a positive influence on the estimated elasticity between hours of work and robot density, reducing in absolute value an estimated negative elasticity and raising a positive estimate, and (2) a measure of the country's openness also has a positive influence on the estimated elasticity if the country has a better innovation system than its trading partners, which is likely for at least the more innovative countries in our sample.

We test these propositions by estimating the correlation between the log of hours $\ln(H_1)$ and log of density $\ln(R/H_1)$ in the robot using sector of the economy, and making the estimate conditional on measures of innovation and trade. The estimated equation is,

$$\begin{aligned} \ln H_{ict} &= \beta_1 \ln(R_{ict}/H_{ict}) + \beta_2 \ln(R_{ict}/H_{ict}) * V_{ct} + \\ &\quad \beta_3 \ln(R_{ict}/H_{ict}) * T_{ct} + \beta_0 + Z_{ict} + \varepsilon_{ict} \end{aligned} \tag{19}$$

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, V_{ct} is the innovation index for each country and T_{ct} is the openness index. The vector Z_{ict} represents country, industry and year fixed effects, although industry fixed effects turned out to be statistically insignificant and IV estimation failed to converge when they were introduced.

The elasticity with which hours of work respond to an increase in robot density, is $(\beta_1 + \beta_2 V_{ct} + \beta_3 T_{ct})$. Our model predictions are that the estimated β_2 should be positive and the estimated β_3 might be positive or negative depending on the country's trading partners and their relative innovation capabilities index. But given that our sample consists entirely of advanced countries, we would expect the coefficient to be positive, as the countries outside the sample that they are trading with on average have lower innovation indices than their own. The estimate for β_1 is not restricted by the theory but given the discussion around condition (18) we expect it to be negative. We calculate these elasticities for each country at the country sample means of V_{ct} and T_{ct}.

We estimate equation (19) for manufacturing and for the full sample that includes the three non-manufacturing sectors listed in Table 3. We estimate it with OLS as well as with instruments that deal with any endogeneity bias in robot density. Our preferred instrument is robot density in Japan over the sample period of our data (fully defined in the data section of the

Appendix). The instrument is chosen to isolate the impact of technological improvements in the manufacture of robots. We have chosen Japan as it is sufficiently removed from our sample of Europe and the United States, so other common influences are remote, and it is a country with large robot densities in manufacturing. Common influences on hours and robot density might include macro conditions not picked up by the year dummies, responses to natural disasters, or other events unconnected with technology.[20] We also carried out various other robustness tests in the Online Appendix, and briefly summarized at the end of this section.

5.2 Estimates for aggregate manufacturing

Table 4 shows the results when all of manufacturing is aggregated into one. Column 1 shows the elasticity estimate when both innovation capabilities and international trade are excluded, column 2 introduces the impact of the innovation environment and column 3 has the full estimate of interactions with both innovation and trade. The last three columns repeat the estimation with instrumental variables with our preferred instrument, log of robot density in Japan, treating robot density as an endogenous variable. Our total observations for manufacturing are 1001 (7 industries in 13 countries over 11 years) but 24 observations were dropped because they had no reliable data on robots - reported as zero by the IFR.

We estimated the equations with a full set of country fixed effects, which turned out to be significant, given the differences in size of our countries in our sample. Because of the large differences in size between some countries, e.g., German hours are 21.5 times as many as Danish hours and 7.5 times as many as Austrian hours, and United States hours are more than twice as many as German hours, the country dummies that we entered to estimate the country fixed effects completely dominated the statistics on statistical significance of the whole set of estimates. To get a better idea of the significance of the other estimates and the goodness of fit, we computed the F statistics and R^2 from regressions that removed the impact of country dummies, by repeating each regression estimate with dependent variable the log of hours net of the estimated country fixed effects. In Table 4 and the other tables reporting the regression results, the F statistics and the R^2 are the ones computed after we removed the country fixed effects.

[20] We also tested for robustness of the IV estimates with two other instruments, robots in South Korea, another country with high robot density in its manufacturing, and the global stock of robots. Results with the alternative instruments confirm our findings and are discussed in the Online Appendix.

The results show that both the innovation system and openness to foreign trade make a statistically significant contribution in all regressions, with a positive sign. Even after the removal of the country fixed effects, the F statistics are well above their critical values and the Cragg-Donald Wald and Kleibergen-Paap Wald F statistics show that our choice of instrument is good.[21] OLS and IV estimation tell a similar story.

Table 5 calculates the net elasticities at sample means from the OLS estimates for four representative countries, Italy, a large country and big user of robots with the lowest innovation index in our sample, Germany, the biggest European economy, biggest user of robots, and strong exporter of manufacturing goods, Sweden, a smaller European country with high innovation index and a large foreign trade sector, and the United States, the biggest economy and top of the innovation index but one that trades much less than the others.

First, we calculate the elasticities when only the innovation index is included in the regression. The estimates show its strong influence on the net elasticities, with the elasticity for Italy dropping to 0.026 with a large standard error, for Germany and Sweden rising to 0.21 and 0.22 respectively, and for the United Sates rising further to 0.24, which is the highest in the sample when openness is ignored. When openness is introduced, the estimate for Italy drops further, to a negative and statistically imprecise number, because of the low openness index for that country. The German estimate remains approximately the same, at 0.20, whereas the Swedish one rises to 0.24 and United States one falls to 0.19, because of the relatively large trade flows of the former and relatively smaller flows of the latter. Thus, when estimating results for the whole of manufacturing, under the restriction that there are no industry differences in elasticities, we find that although on average the introduction of robots in our economies increases hours of work, in countries with low innovation capabilities and low openness index, the impact is negative.

[21] We employ two key diagnostic statistics: the Cragg-Donald Wald statistic and the Kleibergen-Paap Wald F statistic, to assess the strength of our instrumental variables. The Cragg-Donald Wald statistic assumes identically and independently distributed errors (i.i.d.). In our case the Kleibergen-Paap Wald F statistic is more appropriate because of our use of robust standard errors. This statistic extends the Cragg-Donald statistic to accommodate cases with non-i.i.d. errors, which can include heteroskedasticity, autocorrelation, and clustered data (Olea and Plueger, 2013).

5.3 Estimates for high-tech and low-tech manufacturing

We tested for the aggregation of all manufacturing sectors into one and the aggregation restrictions fail. We separated transport equipment and electronics from the rest of manufacturing and obtained better results. 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, but equality was strongly rejected in the regressions with and without the interactions with innovation and trade.[22] With the three industrial groups treated separately, both the significance of the F statistics and the goodness of fit improve substantially across all regressions, although now both tests for the validity of the instruments show some weaknesses. We discuss alternative instruments in the Online Appendix. In terms of point estimates, the IV estimation with our preferred instrument, log of robot density in Japan, gives results that are most comparable to the OLS estimates, despite the weakening of the Cragg-Donald Wald F statistic and Kleibergen-Paap Wald F statistic in some cases. We continue discussing the implications of the estimation results for net elasticities with reference to the OLS point estimates.

Consider first results for the simple regression without taking into account the innovation system of the country or trade. In column (1) of Table 6, the impact of robot density on hours of work is negative for the transport equipment industry and positive for electronics and the rest of manufacturing. They are all statistically significant.

In column (4) we estimate the same equation using our preferred instrument, robot density in Japan. The results of the IV regression for transport equipment and non-tech sectors are similar to the OLS but for electronics the estimate drops below its standard error.

In column (2) of Table 6 we show OLS estimates when the innovation system is taken into account. The coefficient estimates have the expected sign, with β_1 negative and β_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

[22] In the regressions without interactions the relevant test statistic was $F(2, 963) = 285.24$, and in the one with interactions with V, it was $F(4, 960) = 151.35$.

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 system plays a more important role than in other sectors, driving a bigger impact of robots on 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 0.612 for electronics but only 0.176 for transport equipment and 0.179 for the non-tech industries. The contrast is even bigger with the IV estimates. This is to be expected, as electronics is the most research-driven industrial sector in manufacturing. It is also a producer of new technologies, so it benefits more from a stronger innovation system.

In contrast to electronics, the transport equipment industry is not very sensitive to the innovation system. 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 system in the country still saves some jobs from replacement by robots in this sector, but it does not yield net job creation.

The instrumental variables estimation of the regression with the innovation index is in column (5) of Table 6. Overall, the IV estimation confirms a large role for the innovation index in determining the impact of robot density on hours of work.

The impact of trade is shown in columns (3) and (6) of Table 6. The innovation index estimates are robust to the introduction of trade in both the OLS and IV regressions. Trade has a big influence on electronics in the OLS regression, which drops when we use IV, but remains marginally statistically significant. This contrasts with the low-tech sectors, whose impact is enhanced more than in the OLS estimates. An unusual feature of our estimates of the effect of trade is that the coefficient on openness in the transport equipment sector is negative, although not precisely estimated, indicating that countries that trade in this product are adversely affected by more openness. This may be due to competition from Japan and Korea in this sector, a claim that we cannot test but which is consistent with our model prediction, given that those excluded countries are large users of robots and exporters of cars.

Table 7 shows the net impacts in each of the three sectors for the four representative countries that we used in Table 4 for the aggregate estimates. For Italy, the lowest ranking country, the net coefficient is negative in the electronics and transport equipment industries, but is positive and significant in the low-tech sector. The latter result implies that in these sectors the introduction of robots raises hours of work in all countries, but with the exception of chemicals, robot density in these sectors is very low, so their impact on hours is quantitatively small. In the other two sectors, low-ranking countries lose hours when robots are introduced and high-ranking countries gain, although the net impact on hours depends also on openness to international trade. From the OLS regressions in Table 6 we calculate that the point at which the sign of the net impact of robot density on hours in electronics switches from negative to positive is at $V_{ct} = 4.68$, which is just below the sample mean, whereas in transport equipment it is $V_{ct} = 5.03$, which is just above the mean value. Countries in the middle of the innovation capabilities distribution, like France and the United Kingdom, would experience a trivial impact of robots on hours of work. But Germany, Sweden and the United States increase hours when robot density is increased, especially in electronics and the low-tech sectors. The effect on electronics is largest in Sweden, because of its openness and its high innovation capabilities index.

5.4 Estimates for non-manufacturing industries

Table 8 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.[23] 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 in the IV estimates about the role of the innovation index was, however, 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. Despite this, for manufacturing the results replicate the manufacturing results that we obtained in Table 6. Our main finding is also replicated, namely that both the innovation system of a country and its openness are important

[23] See also footnote 18. Zero entries indicate either very small numbers that are subject to error or missing observations altogether, most likely also because of small numbers. We lose 121 observations altogether, so the total number of observations used in the regressions of Table 8 increase only by 308, instead of the full 429 of the three sectors.

influences on the impact of robots on hours of work in both manufacturing and non-manufacturing.

The result that we consistently get for non-manufacturing is that both the innovation system and openness have a negative influence on the impact of robots on hours. To understand the net impact of robot density on non-manufacturing hours, the two effects have to be considered together. We find that the net effect of robot density on hours of work in these sectors is negative. For example, the net elasticity in Germany is -0.39 and in the United States -0.32. The negative elasticities and the weak contribution of the innovation system are not surprising, given the low research potential in these sectors and their very limited use of robotic technologies.

6 Summary of robustness tests

In the Online Appendix we report several robustness tests of the manufacturing regressions, giving detailed tables with the estimation results. These are of two kinds, tests for the estimation procedure and tests for the choice of some variables.

For estimation procedure we experimented with two alternative instruments, robot density in the Republic of Korea from 2006 to 2016 and the global stock of robots over the same period. Results were similar to the ones that we obtained with our preferred instrument, robot density in Japan.

A second robustness test introduced a full set of industry dummies for the seven manufacturing sectors, and with country dummies either individually or interacted with time effects. None of our results changed because of these alternative specifications.

In a final specification test we re-estimated the model by excluding Germany, a large country and by some margin the biggest user of robots in its manufacturing (see Table 2). Its exclusion made virtually no difference to the estimated coefficients in Table 6.

In a second set of robustness tests we tested alternative specifications of our key variables. There are two other widely-available measures of a country's innovation capabilities, the *Global Innovation Index* and the *Summary Innovation Index* of the *European Innovation Scoreboard*. Both indices are highly correlated with our *World Economic Forum* index, and results did not change when used in place of our index.

Human capital plays an important role in our innovation index and there is a good correlation between our innovation index and the human capital of a country. We tested whether our results are driven by human capital and not by our innovation index, but results were much poorer when a human capital index was used in place (or in addition) to our innovation index.[24]

Next, we tested whether our results change when robot density is replaced by the log of the number of robots. The main message of our results comes through, in the sense that a good innovation system acts to mitigate, or reverse, any negative impact of robots on hours of work.

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 (3) of Table 6 again, with each replacing the national innovation index. All indicators except for some estimated coefficients for the availability of scientists and engineers give statistically significant results that conform to the estimates of Table 6.

7 Conclusions

We have addressed the substitutions between hours of work and robots that have been taking place in the manufacturing sectors (and some non-manufacturing) in advanced industrial economies. Our argument is that to understand the nature and extent of the substitutions we need to look beyond the physical capabilities of robots and humans, and investigate how the institutional structure of the country influences the incentives that firms have. We developed a model of a firm with two types of activities, one in which robots and human labour are close substitutes, which we called automatable, and one in which they are complementary to each other. We formalized it as a nested CES production structure, in which the automatable set of activities produces an intermediate good with both human labour and robots, which is then converted into final output with complementary human labour. The model can be given an interpretation that parallels a task-based approach but with only two types tasks - one in which robots are strong substitutes for human labour and one in which they are complements.

Firms choose hours of work and robots to produce the intermediate good and another set of hours to convert the intermediate good to final output. The institutional structure that influences their choices is the "innovation system" of the country, which summarizes the country's innovation capabilities. We made the key assumption that a country with a better innovation system is more productive in the automatable part of production, in which the modern technology, in the form of robots, is employed. We have then shown that in an equilibrium setting, the robot-using sector of a more innovative country is more likely to increase hours of work, or reduce them by less, when robots become relatively cheaper to employ than human labour. This works

[24]See footnote 17 for the definition and source of the human capital variable.

through two channels, both of which, in our equilibrium setting, are driven by relative prices. When the relative cost of employing robots falls, manufacturers in the country with the better innovation system are able to reduce their relative price by more than in the country with the poorer innovation system, because of their more productive automatable production. Domestically, this increases by more the demand for their goods, which increases the demand for non-automatable labour. (Automatable labour always falls when the relative cost of employing robots falls.) The second channel is foreign trade. As relative prices of manufactures fall by more in the country with a better innovation system, domestic demand switches from imported goods to domestic goods and exports rise. The final outcome depends on several elasticities, and in a discussion of elasticity estimates in the literature we concluded that the stronger channel is foreign trade. The countries that are at the most advantageous position to increase, or reduce by less, hours of work when the relative cost of robots falls are therefore the ones that have a large foreign trade sector and a strong innovation system.

In tests with annual data from seven manufacturing sectors over 2006-16 we found strong evidence for these claims. Countries like Germany and Sweden respond positively to an increase in robot density, driven by the fall in the relative price of robots. France, Britain and other countries close to the mean values of the innovation index are less responsive to the arrival of robots, whereas Italy and the Czech Republic might reduce hours, because of their poor innovation systems. The United States is closer to the German responses, despite its small fraction of traded manufacturing output, because of its strong innovation system.

We found that in electronics and electrical equipment, an important research sector, the innovation environment plays a more important role than in other sectors. In contrast, transport equipment, which is the biggest user of robots, substitutes robots for hours more than other sectors do. We also found substitutions between robots and hours of work in three non-manufacturing production sectors, agriculture, mining and utilities. These sectors are very small users of robots, they generally employ large numbers of workers, and they are not strong innovation sectors. We found that virtually all countries reduced hours in these sectors in response to robot introductions.

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 the country's innovation system and its openness but there could be others that future work might be able to identify.

8 Appendix

8.1 Derivations

The profit of the firm in sector 1 is

$$\Pi = p_1 Y_1 - \rho W R - W(H_{1R} + H_{1N}), \tag{20}$$

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

$$p_1 A_1 (1-\beta) \left(\frac{Y_1}{A_1 F}\right)^{1/\sigma} (1-\alpha) V \left(\frac{F}{VR}\right)^{1/s} = \rho W, \tag{21}$$

$$p_1 A_1 (1-\beta) \left(\frac{Y_1}{A_1 F}\right)^{1/\sigma} \alpha V \left(\frac{F}{V H_{1R}}\right)^{1/s} = W, \tag{22}$$

$$p_1 A_1 \beta \left(\frac{Y_1}{A_1 H_{1N}}\right)^{1/\sigma} = W. \tag{23}$$

Dividing (21) by (22) we get the robot density in the automatable part of production,

$$\frac{R}{H_{1R}} = \left(\frac{1-\alpha}{\alpha\rho}\right)^s. \tag{24}$$

Dividing (22) by (23) we get,

$$\frac{H_{1N}}{H_{1R}} = V^{1-\sigma} \left(\frac{\beta}{1-\beta}\right)^\sigma \alpha^{-s} q^{s-\sigma}, \tag{25}$$

with q defined by,

$$q(\rho) \equiv \left[\alpha^s + (1-\alpha)^s \rho^{1-s}\right]^{1/(s-1)}, \qquad q'(\rho) < 0. \tag{26}$$

The function $q(\rho)$ is a uniquely defined function of ρ, given the fixity of α and s. Higher q (lower relative robot price) raises H_{1N}/H_{1R} under the restriction $s > \sigma$. Higher V also raises the ratio H_{1N}/H_{1R}, under the restriction $\sigma < 1$.

Robot density in sector 1 is given by

$$\frac{R}{H_1} = \frac{R}{H_{1R}} \frac{1}{1 + H_{1N}/H_{1R}}, \tag{27}$$

or alternatively,

$$\frac{R}{H_1} = \frac{(1-\alpha)^s \alpha^{-s} \rho^{-s}}{1 + V^{1-\sigma} \beta^\sigma (1-\beta)^{-\sigma} \alpha^{-s} q(\rho)^{s-\sigma}}. \tag{28}$$

Proof of Proposition *1.* Differentiation of (28) with respect to ρ, given the definition of $q(\rho)$, yields the result that lower ρ raises density R/H_1. To show that lower ρ raises hourly productivity, we make use of conditions (24) and (25), to get,

$$\begin{aligned} F &= \alpha^{-s} q(\rho)^s V H_{1R}, && (29)\\ Y_1 &= A_1 H_{1N} \beta^{-\sigma} X^{\sigma/(\sigma-1)}, && (30)\\ X &\equiv V^{\sigma-1} q^{\sigma-1} (1-\beta)^{\sigma} + \beta^{\sigma}. && (31) \end{aligned}$$

Hourly productivity Y_1/H_1 is given by

$$\frac{Y_1}{H_1} = A_1 \frac{H_{1N}}{H_1} \beta^{-\sigma} X^{\sigma/(\sigma-1)}, \tag{32}$$

with

$$\frac{H_{1N}}{H_1} = \frac{1}{1 + H_{1R}/H_{1N}}. \tag{33}$$

which by differentiation with respect to ρ, given the expressions in (25), (26) and (31) gives the results.

To derive the impact of ρ on relative prices we state the marginal productivity condition of firms in sector 2, which, by the linearity of the production function is,

$$p_2 A_2 = W. \tag{34}$$

We divide (23) by (34), and then use (30) to substitute out Y_1, to get

$$\frac{p_1 A_1}{p_2 A_2} X^{1/(\sigma-1)} = 1. \tag{35}$$

Differentiation of (35) with respect to ρ immediately yields the result.

This completes the proof of Proposition 1. We note that these results were derived from the first-order conditions of the firm's maximum, without making use of the equilibrium conditions.

Derivation of equation *(16).* To derive (16) and complete the equilibrium we first derive the marginal rate of substitution between the two goods, obtained from the consumer maximization,

$$\begin{aligned} \frac{c_1}{c_1^*} &= \left(\frac{\psi}{1-\psi}\right)^{\eta} \left(\frac{p_1}{p_1^*}\right)^{-\eta} && (36)\\ \frac{\tilde{c}_1}{c_2} &= \left(\frac{\omega}{1-\omega}\right)^{\varepsilon} \left(\frac{\tilde{p}_1}{p_2}\right)^{-\varepsilon} && (37)\\ \tilde{p}_1 &= \left[\psi^{\eta} p_1^{1-\eta} + (1-\psi)^{\eta} p_1^{*1-\eta}\right]^{1/(1-\eta)} && (38) \end{aligned}$$

From these we get,

$$\frac{c_1}{c_2} = \left(\frac{\tilde{c}_1}{c_1}\right)^{-1}\left(\frac{\tilde{c}_1}{c_2}\right) \tag{39}$$

$$= \left(\frac{\tilde{c}_1}{c_1}\right)^{-1}\left(\frac{\omega}{1-\omega}\right)^{\varepsilon}\left(\frac{\tilde{p}_1}{p_2}\right)^{-\varepsilon} \tag{40}$$

$$= \left(\frac{\omega}{1-\omega}\right)^{\varepsilon}\left(\frac{p_1}{p_2}\right)^{-\varepsilon}\left(\frac{\tilde{p}_1}{p_1}\right)^{-\varepsilon}\left(\frac{\tilde{c}_1}{c_1}\right)^{-1} \tag{41}$$

$$= \left(\frac{\omega}{1-\omega}\right)^{\varepsilon}\left(\frac{p_1}{p_2}\right)^{-\varepsilon}\psi^{\eta}\left(\frac{\tilde{p}_1}{p_1}\right)^{\eta-\varepsilon}. \tag{42}$$

From (35),

$$\left(\frac{p_1}{p_2}\right)^{-\varepsilon} = \left(\frac{A_2}{A_1}\right)^{-\varepsilon} X^{\frac{\varepsilon}{\sigma-1}}, \tag{43}$$

and from (9), (30) and (3),

$$\frac{c_1}{c_2} = \frac{Y_1 - c_1^{**}}{Y_2} \tag{44}$$

$$= \frac{A_1}{A_2}\frac{H_{1N}}{H_2}\beta^{\sigma}X^{\frac{\sigma}{\sigma-1}}\left(1-\frac{c_1^{**}}{Y_1}\right), \tag{45}$$

which together yield,

$$\frac{H_{1N}}{H_2} = A\beta^{\sigma}X^{\frac{\varepsilon-\sigma}{\sigma-1}}\left(\frac{\tilde{p}_1}{p_1}\right)^{\eta-\varepsilon}\left(1-\frac{c_1^{**}}{Y_1}\right)^{-1} \tag{46}$$

Given now that

$$\frac{H_1}{H_2} = \frac{H_{1N}}{H_2}\left(1+\frac{H_{1R}}{H_{1N}}\right), \tag{47}$$

equations (46), (47) and (25) deliver (16) of the text.

Proof of Proposition *2.* Given the derivation of (16), demonstration of this Proposition involves straightforward differentiation, as sketched out in the text, and is not repeated here.

Proof of Proposition *4.* To complete the proof we need to derive the impact of a change in the price of robots on p_1^*/p_1. From (17),

$$\frac{p_1^*}{p_1} = \frac{A_1 X^{1/(\sigma-1)}}{A_1^* X^{*1/(\sigma-1)}} \tag{48}$$

$$= \frac{A_1}{A_1^*}\frac{V^{\sigma-1}q^{\sigma-1}(1-\beta)^{\sigma}+\beta^{\sigma}}{V^{*\sigma-1}q^{\sigma-1}(1-\beta)^{\sigma}+\beta^{\sigma}}. \tag{49}$$

Differentiation with respect to q shows that the sign of the derivative is the same as the sign of

$$(\sigma - 1)\left(V^{\sigma-1} - V^{*\sigma-1}\right), \tag{50}$$

which for $V > V^*$ is positive for all values of $\sigma \neq 1$ (as we noted earlier, for $\sigma = 1$, V has no impact on hours). This completes the proof.

8.2 Data: Definitions and sources

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

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. See Schwab (2017).

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

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.

Trade openness - Given by the sum of manufacturing imports and exports divided by manufacturing output in million dollars. Manufacturing imports, exports and output are obtained from the Input-Output Tables (IOTs) of the OECD (2021), listed by country and year in million dollars.

Table 1. Manufacturing trade flows, sample means, and price elasticities estimates.

Country	Imports percent Manufacturing	Exports percent Manufacturing	Import elasticities	Export elasticities
Austria	46.09	51.24	0.71	1.77
Belgium	42.96	52.22	1.28	1.81
Czechia	44.20	52.97		
Denmark	50.32	48.80		
Finland	30.81	44.32	2.41	1.62
France	42.24	38.64	1.74	1.67
Germany	26.83	41.39	1.34	1.67
Italy	24.84	30.61	2.80	1.60
Netherlands	34.73	49.81		
Spain	34.84	31.89	1.72	1.93
Sweden	39.57	51.55	1.33	1.81
UK	49.77	30.72	1.21	1.54
USA	26.33	15.63	2.01	1.16

Sources

Exports of domestically produced manufacturing goods, gross, imports of manufacturing goods and manufacturing output, all from Input-Output tables, WIOD database, November 2021 release. OECD (2021).

Elasticity estimates from Imbs and Mejean (2010), tables 2 and 8.

Table 2. Country means of key variables.

Country	Innovation Index scale 1-7	Annual Hours (millions)	Robot density	
			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 the annual average of total hours 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 in millions, again for the sectors in the sample.

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

Table 3. Industry means of key variables.

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

Notes

Annual hours are the annual average of hours of work in each sector for all countries.

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 reported are included.

Table 4. Results for aggregate manufacturing

	Dependent variable in all regressions: $\ln H_{ict}$ (log hours by country, industry, and year).					
	(1) OLS	(2) OLS	(3) OLS	(4) IV	(5) IV	(6) IV
$\ln(R_{ict}/H_{ict})$	0.152	-0.445	-0.577	0.190	-0.596	-0.795
	(0.010)	(0.065)	(0.072)	(0.018)	(0.079)	(0.084)
$\ln(R_{ict}/H_{ict}) \ * V_{ct}$		0.124	0.130		0.163	0.164
		(0.013)	(0.013)		(0.017)	(0.016)
$\ln(R_{ict}/H_{ict}) \ * T_{ct}$			0.131			0.252
			(0.047)			(0.065)
Number of obs.	977	977	977	977	977	977
F(11, 965)	21.92			12.76		
F(12, 964)		29.92			18.55	
F(13, 963)			30.67			18.66
R^2	0.22	0.28	0.29	0.21	0.26	0.27
Cragg-Donald Wald F statistic				977.8	489.4	252.1
Kleibergen-Paap Wald F statistic				685.9	342.5	118.7

Notes

Other controls: time and country dummies. The test statistics (F and R^2) are for the significance of the estimated coefficients excluding country fixed effects.

The instrument used is robot density in Japan over the period of the sample. Robust standard errors in parentheses.

Table 5. Net elasticity estimates for aggregate manufacturing

Italy		
	no interactions	0.152
		(0.010)
	interactions with V only	0.026
		(0.017)
	Interactions with V and T	-0.010
		(0.018)
Germany		
	no interactions	0.152
		(0.010)
	interactions with V only	0.211
		(0.012)
	Interactions with V and T	0.201
		(0.011)
Sweden		
	no interactions	0.152
		(0.010)
	interactions with V only	0.220
		(0.012)
	Interactions with V and T	0.241
		(0.014)
United States		
	no interactions	0.152
		(0.010)
	interactions with V only	0.237
		(0.013)
	Interactions with V and T	0.194
		(0.019)

Notes. Net estimates derived from the OLS estimates in Table 4. Robust standard errors in parentheses.

Table 6. Results for manufacturing industries, disaggregated.

	Dependent variable in all regressions: $\ln H_{ict}$ (log hours by country, industry, and year).					
	(1) OLS	(2) OLS	(3) OLS	(4) IV	(5) IV	(6) IV
$\ln(R_{ict}/H_{ict}) * I_1$	0.121	-1.677	-2.505	0.040	-2.724	-3.111
	(0.025)	(0.239)	(0.210)	(0.042)	(0.376)	(0.356)
$\ln(R_{ict}/H_{ict}) * I_2$	-0.026	-0.518	-0.517	-0.027	-0.459	-0.462
	(0.012)	(0.061)	(0.062)	(0.014)	(0.065)	(0.067)
$\ln(R_{ict}/H_{ict}) * I_3$	0.299	-0.209	-0.402	0.440	-0.478	-0.884
	(0.011)	(0.062)	(0.062)	(0.022)	(0.102)	(0.114)
$\ln(R_{ict}/H_{ict}) * I_1 * V_{ct}$		0.358	0.429		0.551	0.577
		(0.047)	(0.037)		(0.070)	(0.071)
$\ln(R_{ict}/H_{ict}) * I_2 * V_{ct}$		0.103	0.117		0.091	0.104
		(0.014)	(0.015)		(0.014)	(0.015)
$\ln(R_{ict}/H_{ict}) * I_3 * V_{ct}$		0.105	0.118		0.191	0.187
		(0.013)	(0.011)		(0.023)	(0.020)
$\ln(R_{ict}/H_{ict}) * I_1 * T_{ct}$			0.610			0.345
			(0.104)			(0.177)
$\ln(R_{ict}/H_{ict}) * I_2 * T_{ct}$			-0.087			-0.071
			(0.046)			(0.047)
$\ln(R_{ict}/H_{ict}) * I_3 * T_{ct}$			0.164			0.541
			(0.052)			(0.103)
Number of obs.	977	977	977	977	977	977
$F(13, 963)$	68.42			57.98		
$F(16, 960)$		75.68			68.96	
$F(19, 957)$			84.90			68.17
R^2	0.51	0.56	0.58	0.39	0.41	0.40
Cragg-Donald Wald *F* statistic				252.1	86.1	40.3
Kleibergen-Paap Wald *F* statistic				161.7	10.4	3.5

Notes

Subscript 1 denotes electronics,2 transport equipment, and 3 low-tech industries.
Other controls: year and country dummies. The test statistics (*F* and R^2) are for the significance of the estimated coefficients excluding country fixed effects.
The instrument used is robot density in Japan over the period of the sample. Robust standard errors in parenthesis.

Table 7. Net elasticity estimates for three industrial groups

	electronics	transport equipment	other (low-tech) sectors
Italy			
no interactions	0.121	-0.026	0.299
	(0.025)	(0.012)	(0.011)
interactions with V only	-0.321	-0.128	0.187
	(0.068)	(0.012)	(0.016)
Interactions with V and T	-0.541	-0.123	0.136
	(0.057)	(0.012)	(0.016)
Germany			
no interactions	0.121	-0.026	0.299
	(0.025)	(0.012)	(0.011)
interactions with V only	0.213	0.025	0.344
	(0.028)	(0.016)	(0.013)
Interactions with V and T	0.177	0.040	0.334
	(0.021)	(0.016)	(0.012)
Sweden			
no interactions	0.121	-0.026	0.299
	(0.025)	(0.012)	(0.011)
interactions with V only	0.241	0.033	0.352
	(0.029)	(0.017)	(0.013)
Interactions with V and T	0.349	0.029	0.380
	(0.035)	(0.017)	(0.014)
United States			
no interactions	0.121	-0.026	0.299
	(0.025)	(0.012)	(0.011)
interactions with V only	0.290	0.047	0.366
	(0.031)	(0.018)	(0.014)
Interactions with V and T	0.108	0.088	0.316
	(0.033)	(0.026)	(0.021)

Notes. Net estimates derived from the OLS estimates in Table 6. Robust standard errors in parentheses.

Table 8. Results for manufacturing and non-manufacturing industries

	Dependent variable in all regressions: $\ln H_{ict}$ (log hours by country, industry, and year).		
	(1) OLS	(2) OLS	(3) OLS
$\ln(R_{ict}/H_{ict}) * I_1$	0.054	-1.810	-2.102
	(0.024)	(0.185)	(0.186)
$\ln(R_{ict}/H_{ict}) * I_2$	-0.033	-0.427	-0.339
	(0.014)	(0.073)	(0.076)
$\ln(R_{ict}/H_{ict}) * I_3$	0.250	-0.135	-0.117
	(0.012)	(0.065)	(0.071)
$\ln(R_{ict}/H_{ict}) * I_4$	-0.362	-0.070	0.228
	(0.037)	(0.152)	(0.190)
$\ln(R_{ict}/H_{ict}) * I_1 * V_{ct}$		0.371	0.404
		(0.035)	(0.033)
$\ln(R_{ict}/H_{ict}) * I_2 * V_{ct}$		0.082	0.094
		(0.017)	(0.019)
$\ln(R_{ict}/H_{ict}) * I_3 * V_{ct}$		0.079	0.090
		(0.014)	(0.013)
$\ln(R_{ict}/H_{ict}) * I_4 * V_{ct}$		-0.061	-0.075
		(0.031)	(0.032)
$\ln(R_{ict}/H_{ict}) * I_1 * T_{ct}$			0.143
			(0.098)
$\ln(R_{ict}/H_{ict}) * I_2 * T_{ct}$			-0.187
			(0.065)
$\ln(R_{ict}/H_{ict}) * I_3 * T_{ct}$			-0.091
			(0.059)
$\ln(R_{ict}/H_{ict}) * I_4 * T_{ct}$			-0.318
			(0.082)
Number of obs.	1285	1285	1285
F(15, 1269)	41.22		
F(19, 1265)		46.88	
F(23,1261)			45.49
R^2	0.32	0.34	0.35

Notes

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

Other controls: year and country dummies and a non-manufacturing dummy. Robust standard errors in parentheses.

The test statistics (F and R^2) are for the significance of the estimated coefficients excluding country fixed effects.

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Online Appendix of Productive Robots and Industrial Employment: The Role of National Innovation Systems

Chrystalla Kapetaniou
University of Southampton, Great Britain

Christopher A Pissarides
London School of Economics, Great Britain
and University of Cyprus, Cyprus

In this Online Appendix we report several robustness tests, to test the estimation procedure and choice of some variables that we used in the main regressions. We begin with the estimation method and sample and we follow with tests for alternative measures of innovation performance, using education variables instead of our summary innovation index, rerun the main regression in levels of robots instead of robot density, and decomposing our innovation index into its six components and rerunning the regression for each separately.

1 Estimation procedure and sample

1.1 Alternative instruments and fixed effects

To further assess the robustness of our basic equation estimates and to address a potential concern regarding the strength of the instrumental variable (IV) employed, which is identified in the analysis presented in Column 6 of Table 6, we computed additional estimates using two alternative instruments: the stock of robots in the Republic of Korea from 2006 to 2016, and the global stock of robots over the same period. The justification is similar to our preferred instrument of robots in Japan. Given that the Republic of Korea is recognized for having the biggest robot densities in manufacturing worldwide, the utilization of the first alternative instrument offers a relevant measure of technological trends across industries. The Republic of Korea's distance from our sample regions, Europe and the United States, minimizes the likelihood of experiencing common industrial shocks. The global stock of robots, our second alternative instrument, reflects the supply and demand dynamics in the robot market. An increase in the global stock indicates enhanced availability and potentially lower prices, which can be attributed to economies of scale and technological progress. These factors are critical in determining robot adoption and density in our sample.

Our findings, presented in Table A.1, reinforce the validity of these instrumental variables. The F statistics obtained exceed the commonly accepted threshold of 10, as suggested by Staiger and Stock (1997), and exceed the 10% critical value identified in the weak instrument test proposed by Stock and Yogo (2005). Moreover, the regression results across these instruments are consistent with each other, further affirming the point estimates in our basic regression.

The results reported so far introduce time fixed effects but not industry effects. We repeated the estimation with a full set of industry dummies for the three sectors and obtained very similar results. These results should be compared with the results in the third column of Table 6 in the main paper. In the first three columns of Table A.2, we report the results with the three industry dummies - electronics, transport equipment, and low-tech industries - either individually or interacted with time effects. We also tested the case in which country dummies are interacted with time effects, reported in the third column of Table A.2, with virtually no change in the results.

1.2 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 between 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 2). We re-estimated our main regression by excluding Germany in the last column of Table A.2, but this made virtually no difference to the estimated coefficients in Table 6.

2 Alternative measures of variables

2.1 Alternative measures of innovation performance

There are two other widely-available measures of a country's innovation system, 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 they 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 column 3 of Table 6. In the interests of space we do not report the estimated regressions but give in Table A.3 only some key coefficients for the net effects. Statistical significance for the point estimates is comparable to that for the regressions in Table 6.[1]

We give the net elasticity estimates for Italy, Germany and the United States (for the WEF index that we used in the main text 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. It is clear that with minor exceptions, our estimates can be replicated with alternative indices for a country's innovation system 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.

2.2 Education performance

Our key innovation system variable is a summary statistic that captures the network of institutions, including universities, industrial research units and other technical and scientific establishments, whose activities and interactions affect the technological development of an economy. As we pointed out in the Introduction to the paper, it embodies the flow of knowledge among individuals, organizations, and institutions. Human capital plays an important role in the compilation of our index and the question that we investigate here is whether a human capital variable for each country plays the same role in our regressions as our innovation variable. In other words, whether we are capturing the influence of something more than human capital in our innovation index variable V.

We re-estimated the main regressions in Tables 4 and 6 by introducing an annual human capital index for each country, defined as the percentage of 25-64 year-olds with tertiary education. The source is OECD (2022). In Table A.4., we show that when the human capital index is added to the model, the innovation index remains significant. When the innovation index is replaced by the human capital index, statistical significance levels drop. When both the innovation index and the education index are entered together, the coefficient on the innovation index remains positive and strong, whereas the coefficient on the education index becomes negative and statistically insignificant.

In Table A.5., we separated transport equipment and electronics from the rest of the manufacturing sector. When the human capital index is included in the regression, the innovation index consistently shows a significant

[1] 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.

positive impact across all industries, whereas human capital displays a more mixed and less consistent impact. As with aggregate manufacturing, when the innovation index is substituted with the human capital index, the results show a reduced level of significance. In electronics, the influence of education becomes negative. Similarly, in the transport equipment sector, a higher human capital index also has a negative impact, albeit less significant.

2.3 Level of robots

Next, we report the main regressions in Table 6 when robot density is replaced by the log of the number of robots. The results are in Table A.6. The main message comes through in the sense that a good innovation system acts to mitigate, or reverse, any negative impact of robots on hours of work. This result is statistically significant in both the OLS estimate and the IV estimate. But a difference in the point estimates that runs through all regressions in Table A.6 is that the impact of robots on hours is not negative and statistically significant even in the countries with the weakest innovation systems. When estimated with the level of robots, our model implies less substitution between robots and hours of work than when estimated with robot density.

2.4 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 3 of Table 6 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 A.7.

All indicators except for some estimated coefficients for the availability of scientists and engineers give statistically significant results that conform to the estimates of Table 6. 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.

3 Data used in this Appendix only

Innovation Index – Two additional composite indicators were used in this Appendix, 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 – Two additional instrumental variables were used: the annual stock of robots in the Republic of Korea and the annual global stock of robots, covering the period from 2006 to 2016. Source: IFR (2017).

Human Capital Index – The Human Capital Index is the annual education level of adults per country, defined as individuals with tertiary education as a percentage of all individuals aged 25-64 from 2006 to 2016. Source: OECD (2022).

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Table A.1. Alternative instruments for manufacturing industries

	Dependent variable in all regressions: $\ln H_{ict}$, log hours by country, industry and year.		
	(1) IV	(2) IV	(3) IV
$\ln(R_{ict}/H_{ict}) * I_1$	-3.111	-2.973	-3.102
	(0.356)	(0.304)	(0.318)
$\ln(R_{ict}/H_{ict}) * I_2$	-0.462	-0.453	-0.462
	(0.067)	(0.088)	(0.074)
$\ln(R_{ict}/H_{ict}) * I_3$	-0.884	-0.470	-0.419
	(0.114)	(0.055)	(0.057)
$\ln(R_{ict}/H_{ict}) * I_1 * V_{ct}$	0.577	0.544	0.569
	(0.071)	(0.058)	(0.062)
$\ln(R_{ict}/H_{ict}) * I_2 * V_{ct}$	0.104	0.102	0.103
	(0.015)	(0.019)	(0.017)
$\ln(R_{ict}/H_{ict}) * I_3 * V_{ct}$	0.187	0.129	0.112
	(0.020)	(0.011)	(0.012)
$\ln(R_{ict}/H_{ict}) * I_1 * T_{ct}$	0.345	0.414	0.377
	(0.177)	(0.172)	(0.173)
$\ln(R_{ict}/H_{ict}) * I_2 * T_{ct}$	-0.071	-0.057	-0.065
	(0.047)	(0.053)	(0.049)
$\ln(R_{ict}/H_{ict}) * I_3 * T_{ct}$	0.541	0.288	0.334
	(0.103)	(0.059)	(0.058)
Number of obs.	977	977	977
F(19, 957)	68.17	81.07	85.99
R^2	0.40	0.53	0.52
Cragg-Donald Wald F statistic	40.28	32.64	34.98

Kleibergen-Paap Wald F statistic	3.54	41.25	55.32

Notes

Subscript 1 denotes electronics,2 transport equipment, and 3 low-tech industries.

Other controls: time and country dummies. The test statistics (F and R^2) are for the significance of the estimated coefficients excluding country fixed effects.

The instrument used in Column (1) is robot density in Japan, in Column (2) stock of robots in Korea and in Column (3) the global stock of robots.

Table A.2. Alternative specifications for manufacturing industries

	Dependent variable in all regressions: $\ln H_{ict}$, log hours by country, industry and year.			
	Industry	Interaction Industry and Year	Interaction Country and Year	Excl. Germany
$\ln(R_{ict}/H_{ict}) * I_1$	-2.199	-2.298	-2.680	-2.501
	(0.181)	(0.193)	(0.251)	(0.222)
$\ln(R_{ict}/H_{ict}) * I_2$	-0.418	-0.416	-0.570	-0.433
	(0.054)	(0.055)	(0.074)	(0.064)
$\ln(R_{ict}/H_{ict}) * I_3$	-0.391	-0.387	-0.492	-0.392
	(0.061)	(0.061)	(0.078)	(0.062)
$\ln(R_{ict}/H_{ict}) * I_1 * V_{ct}$	0.416	0.432	0.454	0.414
	(0.031)	(0.033)	(0.044)	(0.040)
$\ln(R_{ict}/H_{ict}) * I_2 * V_{ct}$	0.134	0.133	0.126	0.080
	(0.014)	(0.014)	(0.017)	(0.014)
$\ln(R_{ict}/H_{ict}) * I_3 * V_{ct}$	0.113	0.112	0.132	0.113
	(0.011)	(0.011)	(0.015)	(0.012)
$\ln(R_{ict}/H_{ict}) * I_1 * T_{ct}$	0.522	0.530	0.693	0.663
	(0.109)	(0.108)	(0.118)	(0.099)
$\ln(R_{ict}/H_{ict}) * I_2 * T_{ct}$	-0.009	-0.036	-0.069	-0.005
	(0.045)	(0.043)	(0.054)	(0.042)
$\ln(R_{ict}/H_{ict}) * I_3 * T_{ct}$	0.171	0.174	0.203	0.175
	(0.050)	(0.050)	(0.049)	(0.050)
Number of obs.	977	977	977	977
$F(21, 955)$	97.51			
$F(41, 935)$		51.07		
$F(151, 825)$			15.52	
$F(19, 880)$				82.29
R^2	0.61	0.62	0.60	0.59

Notes

Subscript 1 denotes electronics,2 transport equipment, and 3 low-tech industries.

Other controls include year, country, and industry dummies in the 'Industry' column. For the 'Interaction Industry and Year' column, country dummies and the interaction term of industry and year dummies are included. In the 'Interaction Country and Year' column, country dummies and the interaction term of country and year dummies are accounted for. The 'Excl. Germany' column includes year and country dummies. Robust standard errors in parentheses. The test statistics (*F* and R^2) are for the significance of the estimated coefficients excluding country fixed effects.

Table A.3. Net coefficient estimates with alternative innovation indices.

	Index	Italy	Germany	US/Sweden
Electronics	**WEF**	-0.541	0.177	0.108
	GII	-0.436	0.145	0.139
	EU	-0.296	0.277	0.451
Transport Equipment	**WEF**	-0.123	0.040	0.088
	GII	-0.131	0.028	0.089
	EU	-0.076	0.068	0.077
Non-tech	**WEF**	0.136	0.334	0.316
	GII	0.140	0.322	0.323
	EU	0.213	0.377	0.420

Notes

The table shows the net coefficient estimated for the impact of robot density on hours of work. See Table 7 for details. The three innovation indices are the World Economic Forum (WEF, as in Table 7), Global Innovation Index (GII) and the European Union Summary Index (EU).

Table A.4. Results for aggregate manufacturing with education

	Dependent variable in all regressions: $\ln H_{ict}$, log hours by country, industry and year.						
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS	(7) OLS
$\ln(R_{ict}/H_{ict})$	0.152	-0.445	0.011	-0.577	-0.117	-0.468	-0.582
	(0.010)	(0.065)	(0.029)	(0.072)	(0.052)	(0.067)	(0.072)
$\ln(R_{ict}/H_{ict}) * V_{ct}$		0.124		0.130		0.136	0.135
		(0.013)		(0.013)		(0.017)	(0.016)
$\ln(R_{ict}/H_{ict}) * T_{ct}$				0.131	0.136		0.128
				(0.047)	(0.049)		(0.047)
$\ln(R_{ict}/H_{ict}) * E_{ct}$			0.455		0.524	-0.115	-0.044
			(0.093)		(0.090)	(0.113)	(0.113)
Number of obs.	977	977	977	977	977	977	977
F(11, 965)	21.92						
F(12, 964)		29.92	22.11				
F(13, 963)				30.67	21.92	29.04	
F(14, 962)							29.34
R^2	0.22	0.28	0.23	0.29	0.24	0.28	0.29

Notes

Other controls: time and country dummies. Robust standard errors in parentheses. The test statistics (*F* and R^2) are for the significance of the estimated coefficients excluding country fixed effects.

Table A.5. Results for manufacturing industries with education, disaggregated

	Dependent variable in all regressions: $\ln H_{ict}$, log hours by country, industry and year.						
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS	(7) OLS
$\ln(R_{ict}/H_{ict}) * I_1$	0.121	-1.677	0.107	-2.505	-0.461	-2.006	-2.729
	(0.025)	(0.239)	(0.025)	(0.210)	(0.140)	(0.275)	(0.188)
$\ln(R_{ict}/H_{ict}) * I_2$	-0.026	-0.518	-0.001	-0.517	-0.079	-0.547	-0.547
	(0.012)	(0.061)	(0.084)	(0.062)	(0.053)	(0.072)	(0.074)
$\ln(R_{ict}/H_{ict}) * I_3$	0.299	-0.209	-0.087	-0.402	-0.054	-0.135	-0.312
	(0.011)	(0.062)	(0.034)	(0.062)	(0.051)	(0.071)	(0.068)
$\ln(R_{ict}/H_{ict}) * I_1 * V_{ct}$		0.358		0.429		0.519	0.563
		(0.047)		(0.037)		(0.073)	(0.058)
$\ln(R_{ict}/H_{ict}) * I_2 * V_{ct}$		0.103		0.117		0.133	0.137
		(0.014)		(0.015)		(0.023)	(0.022)
$\ln(R_{ict}/H_{ict}) * I_3 * V_{ct}$		0.105		0.118		0.065	0.067
		(0.013)		(0.011)		(0.021)	(0.020)
$\ln(R_{ict}/H_{ict}) * I_1 * T_{ct}$				0.610	0.463		0.612
				(0.104)	(0.103)		(0.115)
$\ln(R_{ict}/H_{ict}) * I_2 * T_{ct}$				-0.087	-0.053		-0.061
				(0.046)	(0.044)		(0.045)
$\ln(R_{ict}/H_{ict}) * I_3 * T_{ct}$				0.164	0.167		0.171
				(0.052)	(0.051)		(0.053)
$\ln(R_{ict}/H_{ict}) * I_1 * E_{ct}$			0.382		0.701	-1.477	-1.240

			(0.261)		(0.260)	(0.404)	(0.362)
$\ln{(R_{ict}/H_{ict})} * I_2 * E_{ct}$			0.200		0.305	-0.381	-0.277
			(0.101)		(0.101)	(0.159)	(0.151)
$\ln{(R_{ict}/H_{ict})} * I_3 * E_{ct}$			0.621		0.718	0.385	0.488
			(0.088)		(0.084)	(0.150)	(0.149)
Number of obs.	977	977	977	977	977	977	977
F(13, 963)	68.42						
F(16, 960)		75.68	61.78				
F (19, 957)				84.90	66.24	63.87	
F (22, 954)							77.78
R^2	0.51	0.56	0.52	0.58	0.54	0.57	0.60

Notes

Subscript 1 denotes electronics, 2 transport equipment, and 3 low-tech industries.
Other controls: year and country dummies. Robust standard errors in parentheses. The test statistics (*F* and R^2) are for the significance of the estimated coefficients excluding country fixed effects.

Table A.6. Results for manufacturing industries, robots in levels

	Dependent variable in all regressions: $\ln H_{ict}$, log hours by country, industry and year.			
	(1) OLS	(2) OLS	(3) IV	(4) IV
$\ln(R_{ict}) * I_1$	0.161	-0.300	0.243	-0.286
	(0.009)	(0.038)	(0.013)	(0.039)
$\ln(R_{ict}) * I_2$	0.113	-0.160	0.172	-0.162
	(0.006)	(0.018)	(0.009)	(0.018)
$\ln(R_{ict}) * I_3$	0.210	-0.055	0.290	-0.067
	(0.006)	(0.015)	(0.011)	(0.015)
$\ln(R_{ict}) * I_1 * V_{ct}$		0.062		0.062
		(0.006)		(0.007)
$\ln(R_{ict}) * I_2 * V_{ct}$		0.046		0.048
		(0.003)		(0.003)
$\ln(R_{ict}) * I_3 * V_{ct}$		0.024		0.028
		(0.003)		(0.003)
$\ln(R_{ict}) * I_1 * T_{ct}$		0.270		0.289
		(0.021)		(0.023)
$\ln(R_{ict}) * I_2 * T_{ct}$		0.112		0.127
		(0.013)		(0.014)
$\ln(R_{ict}) * I_3 * T_{ct}$		0.253		0.278
		(0.012)		(0.015)
Number of obs.	977	977	977	977
$F(13, 963)$	94.86		64.22	
$F(19, 957)$		163.96		113.32
R^2	0.51	0.67	0.44	0.66
Cragg-Donald Wald F statistic			274.74	150.29
Kleibergen-Paap Wald F statistic			249.08	109.83

Notes

Other controls: year and country dummies. Subscript 1 denotes electronics,2 transport equipment, and 3 low-tech industries. The instrument used is robots in Japan over the period of the sample. Robust standard errors in parentheses. The test statistics (*F* and R^2) are for the significance of the estimated coefficients excluding country fixed effects.

Table A.7. Components of the innovation index

	Dependent variable in all regressions: $\ln H_{ict}$, log hours by country, industry and year.					
	Innovation Capacity	Scientific research quality	R&D company spending	University industry collaboration	Government Tech procurement	Scientist Engineer available
$\ln(R_{ict}/H_{ict}) * I_1$	-2.198	-1.331	-1.975	-1.572	-1.740	-1.659
	(0.258)	(0.321)	(0.184)	(0.229)	(0.185)	(0.265)
$\ln(R_{ict}/H_{ict}) * I_2$	-0.518	-0.407	-0.399	-0.300	-0.405	-0.225
	(0.076)	(0.043)	(0.052)	(0.047)	(0.069)	(0.144)
$\ln(R_{ict}/H_{ict}) * I_3$	-0.381	-0.352	-0.251	-0.237	-0.169	-0.063
	(0.068)	(0.061)	(0.056)	(0.052)	(0.069)	(0.120)
$\ln(R_{ict}/H_{ct}) * I_1 * V_{ct}$	0.359	0.205	0.332	0.255	0.346	0.260
	(0.045)	(0.049)	(0.033)	(0.037)	(0.044)	(0.042)
$\ln(R_{ict}/H_{ict}) * I_2 * V_{ct}$	0.112	0.091	0.095	0.073	0.103	0.041
	(0.014)	(0.010)	(0.011)	(0.011)	(0.017)	(0.023)
$\ln(R_{ict}/H_{ict}) * I_3 * V_{ct}$	0.111	0.103	0.091	0.086	0.084	0.045
	(0.012)	(0.011)	(0.009)	(0.009)	(0.015)	(0.020)
$\ln(R_{ict}/H_{ict}) * I_1 * T_{ct}$	0.565	0.430	0.562	0.517	0.581	0.567
	(0.102)	(0.111)	(0.089)	(0.114)	(0.097)	(0.109)
$\ln(R_{ict}/H_{ict}) * I_2 * T_{ct}$	-0.091	-0.132	-0.095	-0.101	-0.030	-0.013
	(0.044)	(0.052)	(0.044)	(0.050)	(0.047)	(0.059)
$\ln(R_{ict}/H_{ict}) * I_3 * T_{ct}$	0.152	0.129	0.148	0.147	0.171	0.174
	(0.050)	(0.053)	(0.052)	(0.052)	(0.052)	(0.054)
Number of obs.	977	977	977	977	977	977
F(19, 957)	81.29	74.53	83.41	74.83	78.49	62.59
R^2	0.58	0.56	0.59	0.57	0.56	0.53

Notes

The coefficients in this table were estimated with OLS regressions like the one in column (3) of Table 6, with each of the six components of the *National Innovation Index* replacing the aggregate index in turn. Robust standard errors in parentheses.