Online Appendix for "Robots at Work"

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1 Data Appendix

Imputation of the initial robot stock for a subset of countries

A complicating feature of the IFR data is that for half of the countries in our final sample, a breakdown of deliveries by industries is not available for earlier years in the sample, when all delivered units are reported under the "unspecified" category. These countries (and the year that the breakdown by industries first becomes available) include Australia (2006), Austria (2003), Belgium (2004), Denmark (1996), Greece (2006), Hungary (2004), Ireland (2006), Korea (2001, but not in 2002, then again from 2003 onwards), Netherlands (2004), and the US (2004). For this group of countries, we impute industry-level deliveries by multiplying the number of robots reported as "unspecified" by the average share of an industry's deliveries in total deliveries during the years when the breakdown was reported in the data. To compute the share of deliveries we use all the years available in the IFR data, up to and including 2011. Similarly, for these countries we multiply the stock reported by IFR as "unspecified" in 1993 by the average share of deliveries. We then apply our perpetual inventory method to compute the stock for all subsequent years.

Data on robot prices

The IFR reports two measures of prices: one that is based on the total turnover of the robots producing industries, and one that is based on list prices of surveyed firms. However, the IFR does not report price data for all countries and years. Turnover-based prices are calculated as the ratio of the total turnover of the robots industries and the number of robots delivered. They are available throughout our sample period for the US only, and can be found in International Federation of Robotics (2005) and International Federation of Robotics (2012). For each country-industry-year cell, we compute robot services as the product of the turnover-based US price of robots and our measure of the robot stock, multiplied by 0.15 which is the sum of a depreciation rate of ten percent and a real interest rate of five percent. (This procedure is based on the neoclassical theory of investment, see e.g. Timmer, van Moergastel, Stuivenwold, Ypma, O'Mahony, and Kangasniemi (2007, p.33) for a discussion and application to EUKLEMS capital data.)

As the IFR points out, turnover-based prices are problematic as the total turnover also includes peripherals, customer services, etc., and is affected by volume discounts. For selected countries the IFR also reports price indices based on list prices, but these stop in 2005. List prices, together with data on changes in characteristics of robots, enabled the IFR to construct quality adjusted price indices, as well. We report these indices in Figure 1.

The IFR employed the following method to adjust for changes in quality (International Federation of Robotics, 2006, Annex C). First, it assumed that of the marginal cost of making a robot, 20 percent is due to the control unit (a computer), 40 percent is due to mechanical characteristics that change over time (including payload, accuracy, aggregated speed of all axes, and maximum reach), and the remaining 40 percent is due to time-invariant mechanical characteristics. Given the improvements of computers and mechanical characteristics over time, and assuming that costs are proportional in computer quality and mechanical characteristics, the IFR calculated what a contemporary robot would have cost to produce in the base year, and hence what its price would have been, assuming a constant markup. The quality-adjusted price change is then simply the difference between this counterfactual price and the actual price.

Imputation of initial and final observations

While most EUKLEMS variables are non-missing both in 1993 and 2007 for all countries and industries, there are some exceptions. The breakdown of the labor input by skill groups is not available past 2005 for any country; for Hungary, information on the wage bill, capital inputs, skills, and TFP is not available prior to 1995; for Belgium, information on the wage bill, capital inputs, and TFP is not available after 2006; for South Korea, information on capital inputs is not available after 2005. In each case, we impute 1993 and 2007 values using the closest year for which data are available.

2 Calculation of Magnitudes

We consider a counterfactual scenario in which robot densities (robots per million hours worked) in 2007 would have remained the same as in 1993. We calculate how much lower labor productivity would have been in this case.[1] This calculation is subject to some caveats. Specifically, we do not account for the possibility of spillovers across industries. For example, by growing faster, robot-using industries may have taken up resources that would otherwise have been used by other industries, leading us to overestimate the gains from increased robot use. Or, to take a different example, the increased use of robots may have reduced the price of products sold to other industries and used as inputs, making us underestimate the gains from increased robot densification. Another potential limitation of this counterfactual is that without robot densification, factors may have reallocated differently across industries over time.

To calculate counterfactual productivity, we proceed as follows. We first compute the 'zero-percentile', the percentile of changes in robot density that corresponds to no change, q_0. Let q_{ci} denote the actual percentile of the change in robot density in country c and industry i. We calculate the counterfactual log change of $y \equiv \text{VA/H}$ as $(\Delta \ln y_{ci})^{cf} = \Delta \ln y_{ci} - \widehat{\beta}\,(q_{ci} - q_0)$, where $\widehat{\beta}$ is the preferred estimate of robot densification's role in shaping productivity. Using $(\Delta \ln y_{ci})^{cf}$, we compute the counterfactual log values and levels of productivity in 2007 for each country-industry. We then aggregate levels of productivity to the country level, using as weights an industry's 2007 share in total hours in its country, obtaining $Y^{cf}_{c,2007}$. By comparing these numbers to the actual 2007 levels, we obtain an estimate of how much lower productivity would have been in the absence of robot densification. In particular, we calculate the percentage loss as $100 \times (1 - y^{cf}_{c,2007}/y_{c,2007})$.[2]

We base our analysis on the OLS estimates from the specifications that allow for both coun-

[1] An alternative counterfactual scenario is one in which all country-industries reach the same robot density by 2007 as the country-industry with the maximum robot density in the sample. However, given that many industries have very low shares of replaceable tasks, such a scenario does not seem plausible. In contrast, the fall in robot prices could well have been much slower than it actually was, and industries could have stayed close to their 1993 levels of robot density—this is the scenario that we focus on.

[2] We do not perform standard growth accounting to assess the contribution of robots, because such an exercise requires an aggregate production function that is constant over time. But the adoption of robot technology involves a change in the production function, as evidenced by the absence of robots in many country-industries in 1993, and as illustrated by our model. The model also emphasizes the roles of fixed costs and monopoly rents in robot adoption, and both features are at odds with the assumptions needed for growth accounting.

try and industry trends, setting $\widehat{\beta} = 0.35$.[3] Since this estimate is lower than our 2SLS estimate, the results reported here may be viewed as conservative. The bottom row in Appendix Table A10 shows that the counterfactual loss in labor productivity for the robot-using industries implied by the OLS estimate is on average about 16 percent across countries. We calculate that countries with more rapid robot densification would experience a larger loss in productivity in the absence of robot densification. The loss in both productivity would have been highest for Germany and lowest for Hungary.

What are the implications of increased robot densification for economies as a whole? Assuming that no robots are used in the industries excluded from our sample, we obtain the loss in economy-wide productivity by multiplying our figures for the robot-using industries by the share in value added of the robot-using industries in 2007. This share is typically around one third or less, and hence our estimates of losses in productivity drop substantially. Still, we find that productivity would have been about 5.1 percent lower in the absence of robot densification. This implies that robot densification increased annual growth of labor productivity by about 0.36 percentage points. This figure is roughly comparable to the estimated total contribution of steam technology to British annual labor productivity growth in the nineteenth century, which was around 0.35 percentage points, but was sustained over a period that was about four times longer, from 1850-1910 (Crafts, 2004). The overall contribution of robots is lower than the upper range of estimates of ICT's contribution to EU and US labor productivity growth form 1995-2005, which O'Mahony and Timmer (2009) estimate at 0.6 and 1.0 percentage points, respectively. However, the total value of ICT capital services exceeds that of robot services.[4]

[3] This is taken from panel A, column (4) of Table A8.

[4] Averaged across countries and the years 1993 and 2007, the share of robot services in total capital services is 0.64 percent (2.25 percent in robot-using industries), compared to 11 percent for ICT services (13 percent in robot-using industries). However, the IFR (2012, p.11) points out that their data on the value of the robot stock "do not include the cost of software, peripherals and systems engineering", and that the true value of the robot stock may be three times as large. A further difficulty in this context is that EUKLEMS data break down the capital stock into ICT and non-ICT, but robots are made of both ICT and non-ICT components (even though in the EUKLEMS data they are included in non-ICT capital).

The contribution of robots to growth is also less than that of post-war road construction in the US, which Fernald (1999) estimates at 1 percent for the period 1953-1973.

3 Theory Appendix

Formal derivations and proofs of results from the theoretical model

We first derive equilibrium expressions for profits, using the solutions to the consumers' and firms' optimization problems. Denote a consumer's income—equal to total income in the economy—by I. Given the Dixit-Stiglitz-type setup, utility-maximizing consumption choices take the standard form

$$C(i,j) = \left(\frac{P(i,j)}{P(i)}\right)^{-\eta} C(i), \qquad C(i) = \left(\frac{P(i)}{P}\right)^{-\varepsilon} \frac{I}{P}, \tag{1}$$

where $P(i,j)$ is the price of variety j in industry i, $P(i) \equiv \left(\int_0^1 P(i,j)^{1-\eta} dj\right)^{\frac{1}{1-\eta}}$ is the price index of industry i and $P \equiv \left(\int_0^1 P(i)^{1-\varepsilon} di\right)^{\frac{1}{1-\varepsilon}}$ is the economy-wide price index.

Given the demand curve (1) and the market clearing condition $C(i,j) = Y(i,j)$, the firm producing this variety maximizes profits by setting a price equal to a markup times marginal cost, $P(i,j) = (\eta/(\eta-1))\chi(i,j)$. Under the optimal pricing rule, and using (1), profits equal $\pi(i,j) = \theta P(i)^{\eta-\varepsilon} \chi(i,j)^{-(\eta-1)}$, where $\theta \equiv ((\eta-1)^{\eta-1}/\eta^{\eta}) I P^{\varepsilon-1}$.

For a complete characterization of general equilibrium in our model, we also require the income accounting identity $I = L + \rho \int_0^1 \int_0^1 R(i,j) dj di + \int_0^1 \int_0^1 \pi(i,j) dj di - \varphi \int_0^1 f(i) di$ and the resource constraint $L = \int_0^1 \int_0^1 L(i,j) dj di + \varphi \int_0^1 f(i) di$.

We now state and prove the model's implication for the extensive margin of robot adoption.

Result 1 Robots are only adopted in sectors whose share of replaceable tasks exceeds a critical value. A fall in the fixed cost of robot adoption, or in the rental price, leads to a decrease in this critical value (provided adoption cost and rental price are not too low). Formally, let $f(i)$ denote the fraction of firms that use robots in industry i. $f(i)$ is continuous. Provided $f(i) > 0$ for some i, there exists an $i^* \in (0,1)$ (and an $\alpha^* \equiv \alpha(i^*)$) such that $f(i) = 0 \;\forall i \in [0, i^*]$ and $f(i) > 0 \;\forall i \in (i^*, 1]$. Furthermore, there exist $\widetilde{\rho}, \widetilde{\varphi} > 0$ such that $\partial \alpha^*/\partial \rho > 0 \;\forall \rho \geq \widetilde{\rho}$ and $\partial \alpha^*/\partial \varphi > 0 \;\forall \varphi \geq \widetilde{\varphi}$.

Proof Firms adopt robots when variable profits from doing so exceed variable profits from using labor only by at least the fixed cost of robot use. Formally,

$$\theta P(i)^{\eta-\varepsilon}\left(\chi^R(i,j)^{-(\eta-1)}-\chi^N(i,j)^{-(\eta-1)}\right)\geq\varphi.$$

This expression can be re-written as

$$G(i)\equiv\widehat{\theta}\,[1+f(i)g(i)]^{-\frac{\eta-\varepsilon}{\eta-1}}\,g(i)\geq\varphi, \tag{2}$$

where $\widehat{\theta}\equiv\left(\frac{\eta}{\eta-1}\right)^{\eta-\varepsilon}\theta$, the gap of variable profits between the robot-using and labor-only technologies is given by

$$\begin{aligned} g(i) &\equiv \left(\chi^R(i,j)^{-(\eta-1)}-\chi^N(i,j)^{-(\eta-1)}\right) \\ &= \left[\alpha(i)\rho^{1-\sigma}+1-\alpha(i)\right]^{\frac{1-\eta}{1-\sigma}}-1, \end{aligned} \tag{3}$$

and we used $P(i)=\frac{\eta}{\eta-1}\left[f(i)\chi^R(i)^{1-\eta}+(1-f(i))\chi^N(i)\right]^{\frac{1}{1-\eta}}$ in an intermediate step.

Note that $g(0)=0$, and $g(1)>0$ is ensured by the assumption $\rho<1$, which is indeed required if robots are to be adopted at all. The same assumption ensures $g'(i)>0$. The technology adoption condition implies that $f(i)=0$ unless $g(i)$ is sufficiently positive. Thus we have established that there is some i^* such that $f(i)=0$ for $i\leq i^*$.

We have $\lim_{i\to^- i^*}G(i)=\varphi$ and $\lim_{i\to^- i^*}f(i)=0$. To prove continuity of $f(i)$, assume to the contrary that $\lim_{i\to^+ i^*}f(i)\equiv\widehat{f}>0$. This implies

$$\lim_{i\to^+ i^*}G(i)=\widehat{\theta}\left[1+\widehat{f}g(i^*)\right]^{-\frac{\eta-\varepsilon}{\eta-1}}g(i^*)<\widehat{\theta}g(i^*)=\varphi.$$

But the inequality contradicts the optimality of robot adoption implied by the assumption $\widehat{f}>0$. A similar argument rules out that $f(i)$ attains the value one by a discontinuous jump. And as long as $f(i)\in(0,1)$, it must be continuous because (2) holds with equality and $g(i)$ is continuous.

To prove that $f(i)>0\ \forall i\in(i^*,1]$, suppose that there exists an $i_1>i^*$ such that $f(i_1)=0$.

Then $\widehat{\theta}g(i_1) \leq \varphi = \widehat{\theta}g(i^*)$, which contradicts the fact that $g(i)$ is strictly increasing in i.

Finally, to establish existence of a $\widetilde{\rho} > 0$ such that $\partial\alpha^*/\partial\rho > 0 \;\forall\rho \geq \widetilde{\rho}$ and a $\widetilde{\varphi}$ such that $\partial\alpha^*/\partial\varphi > 0 \;\forall\varphi \geq \widetilde{\varphi}$, note simply that for high enough ρ or ϕ we will have $i^* = 1$, and a fall in either parameter will move the threshold into the interior. The result holds globally if the effects of a fall in ρ or φ on $\widehat{\theta}$ (which is a function of the economy-wide price level as well as total income) are negligible, in which case implicit differentiation of $\widehat{\theta}g(i^*) = \varphi$ yields $\partial\alpha^*/\partial\rho > 0$ and $\partial\alpha^*/\partial\varphi > 0$. ∎

Lastly, we turn to the model's predictions about the effects of increased robot use on sectoral employment. Take two industries i_1 and i_2 and let their fractions of robot-using firms be $f(i_1) = 0$ and $f(i_2) = 1$. If we denote total labor used in industry i by $L(i)$, then we can show that[5]

$$\frac{L(i_2)}{L(i_1)} = (1-\alpha(i_2))\left(\frac{\chi^R(i_2)}{\chi^N(i_1)}\right)^{\sigma-\varepsilon}, \tag{4}$$

and if $f(i_1) = 1$ and $f(i_2) = 1$, then

$$\frac{L(i_2)}{L(i_1)} = \left(\frac{1-\alpha(i_2)}{1-\alpha(i_1)}\right)\left(\frac{\chi^R(i_2)}{\chi^R(i_1)}\right)^{\sigma-\varepsilon}. \tag{5}$$

Recalling that $\chi^R(i_2)/\chi^N(i_1)$ is increasing in ρ, and realizing that $\chi^R(i_2)/\chi^R(i_1)$ is increasing in ρ if and only if $\alpha(i_2) > \alpha(i_1)$, we obtain the following predictions.

Result 2 Suppose $f(i_1) = 0$ and $f(i_2) = 1$. A fall in the rental rate ρ leads to a rise (a fall, no change) in the robot-using industry i_2's employment relative to that of the non-robot-using industry i_1 if and only if $\varepsilon > \sigma$ ($\varepsilon < \sigma$, $\varepsilon = \sigma$). Now suppose $f(i_1) = 1$ and $f(i_2) = 1$ and $\alpha(i_2) > \alpha(i_1)$. A fall in the rental rate ρ leads to a rise (a fall, no change) in the robot-using industry i_2's employment relative to that of the robot-using industry i_1 if and only if $\varepsilon > \sigma$ ($\varepsilon < \sigma$, $\varepsilon = \sigma$). In each case, formally, $\partial\left[L(i_2)/L(i_1)\right]/\partial\rho \lesseqgtr 0 \Leftrightarrow \varepsilon \gtreqless \sigma$.

[5]If $R(i,j) > 0$ then $Y(i,j)/L(i,j) = (1-\alpha(i))^{-1}\left(\chi^R(i)\right)^{-\sigma}$ by (1), (2), and given the optimal robot-to-labor ratio. And if $R(i,j) = 0$ then $Y(i,j)/L(i,j) = 1$ by (1). If technology choice does not vary within an industry, then $L(i,j) = L(i)$. Moreover, $P(i,j) = P(i)$ and so $C(i) = C(i,j) = Y(i,j)$ by (1) and market clearing. Combining the previous results with the demand curve $C(i_2)/C(i_1) = \left(\chi^R(i_2)/\chi^N(i_1)\right)^{-\varepsilon}$ yields (4) and (5).

Calculating the Present Discounted Value and rate of return of robot adoption based on payback time

Let T be the number of months it takes to recover the upfront investment. We will use this information to calculate the present discounted value (PDV) of switching to a robot-using technology, as well as the implied rate of return.

The first step is to calculate the monthly surplus s from using robots. This is the increment in profits due to using robots. We assume that this surplus is constant over the service life of the robot. We normalize s by the amount of the upfront investment (or equivalently, normalize the upfront investment to equal one). Let r denote the interest rate—the rate of return on an alternative, safe investment such as a risk-free bond, and δ the depreciation rate, both annually. In our baseline case, we assume that the flow of additional profits begins one month after the initial investment is made. We later allow for a longer installation period.

If the investment is recovered in T months, we must have

$$1 = s \times (q + q^2 + ... + q^T) = s \times \frac{q - q^{T+1}}{1-q}, \quad \text{where } q \equiv \frac{1-\delta/12}{1+r/12}. \tag{6}$$

This determines the surplus as a function payback time, as well as interest and depreciation rates,

$$s = \frac{1-q}{q-q^{T+1}}. \tag{7}$$

Let K denote the service life of the robot.[6] The PDV is given by

$$PDV = s \times (q + q^2 + ... + q^K) = \frac{1-q^K}{1-q^T}, \tag{8}$$

where the second equality follows from (7). For simplicity, we assume that the robot has no value at the end of its service life. (8) also gives the PDV *relative* to the PDV of investing

[6] We allow for continuous depreciation, e.g. due to wear and tear, as well as for the possibility that use of the robot will be discontinued at some point. This nests some special cases such as constant performance ($\delta = 0$) and infinite service life ($K \to \infty$).

\$1 at interest rate r, because the latter is equal to one for any time horizon, assuming that the initial investment is fully recovered at the end. The PDV of robots is larger than one for any finite payback time (since payback time is less than service life by definition), and this holds independently of the interest and depreciation rates.

The rate of return x is the rate at which we would have to invest our funds in order to obtain the same PDV as the robot generates over its life time. Given that we fully recover the alternative investment at the end, this PDV equals

$$\frac{x}{12} \times (\widetilde{q} + \widetilde{q}^2 + ... + \widetilde{q}^K) + \widetilde{q}^K, \quad \text{where } \widetilde{q} \equiv \frac{1}{1 + r/12}.$$

Equalizing this expression to the PDV of robots as given by (8), we obtain

$$x = \frac{12}{\widetilde{q}} \frac{1 - \widetilde{q}}{1 - \widetilde{q}^K} \left(PDV - \widetilde{q}^K \right). \tag{9}$$

Now suppose that the firm starts receiving the monthly surplus $M \geq 1$ periods after the initial investment. Using similar reasoning as above, we obtain

$$s = \frac{1 - q}{q^M - q^{T+1}}, \qquad PDV = \frac{1 - q^{K-M+1}}{1 - q^{T-M+1}}, \tag{10}$$

which nests the case $M = 1$, as can be seen from comparing (10) to (7) and (8). The calculation of the rate of return is as in (9), with the PDV given by (10).

4 Tables from Paper, Extended

Table P1: Changes in Robots Input and Growth in Productivity 1993-2007—OLS & IV Estimates

	$\Delta \ln(\text{VA/H})$			
	(1)	(2)	(3)	(4)
A. OLS				
Robot adoption	0.36	0.57	0.64	0.66
	(0.23)	(0.27)	(0.22)	(0.24)
B. IV: replaceable hours				
Robot adoption	0.88	0.91	0.99	1.05
	(0.50)	(0.49)	(0.39)	(0.38)
F-statistic	41.8	34.2	33.9	36.8
C. IV: reaching & handling				
Robot adoption	0.69	0.71	0.90	1.02
	(0.56)	(0.53)	(0.45)	(0.42)
F-statistic	30.1	25.0	16.1	19.3
D. IV: replaceable hours, reaching & handling entered jointly				
Robot adoption	0.86	0.89	0.99	1.05
	(0.50)	(0.49)	(0.39)	(0.38)
F-statistic	25.4	19.3	17.4	19.7
J-statistic (*p*-value)	0.55	0.51	0.66	0.86
Country trends		✓	✓	✓
Controls			✓	✓
Changes in other capital				✓
Observations	238	238	238	224

Notes: Robot adoption refers to the percentile in the weighted distribution of changes in robot density, divided by one hundred. Controls include initial (1993) values of log wages and the ratio of capital services to the wage bill. “Changes in other capital” indicates that changes in the ratio of capital services to the wage bill and changes in the ICT share in total capital services are controlled for. Data on the ICT share are missing for Greece in the EUKLEMS data. Robust standard errors, two-way clustered by country and industry, in parentheses. Regressions are weighted by 1993 within-country employment shares.

Table P2: Further Outcomes—TFP and Prices

	$\Delta\ln(\text{TFP})$			$\Delta\ln(\text{P})$		
	(1)	(2)	(3)	(4)	(5)	(6)
A. OLS						
Robot adoption	0.26	0.47	0.47	-0.38	-0.47	-0.51
	(0.20)	(0.19)	(0.19)	(0.18)	(0.20)	(0.21)
B. IV: replaceable hours						
Robot adoption	0.62	0.79	0.79	-0.55	-0.66	-0.72
	(0.40)	(0.32)	(0.32)	(0.47)	(0.35)	(0.35)
F-statistic	47.7	32.7	35.0	41.8	33.9	36.8
C. IV: reaching & handling						
Robot adoption	0.39	0.63	0.64	-0.40	-0.67	-0.71
	(0.46)	(0.37)	(0.36)	(0.56)	(0.43)	(0.38)
F-statistic	39.3	17.3	17.2	30.1	16.1	19.3
D. IV: replaceable hours, reaching & handling entered jointly						
Robot adoption	0.61	0.79	0.79	-0.54	-0.66	-0.72
	(0.40)	(0.32)	(0.32)	(0.47)	(0.35)	(0.35)
F-statistic	29.4	17.2	19.9	25.4	17.4	19.7
J-statistic (*p*-value)	0.34	0.39	0.36	0.58	0.98	0.96
Country trends & controls		✓	✓		✓	✓
Changes in other capital			✓			✓
Observations	210	210	210	238	238	224

Notes: Robot adoption refers to the percentile in the weighted distribution of changes in robot density, divided by one hundred. Controls include initial (1993) values of log wages and the ratio of capital services to the wage bill. "Changes in other capital" indicates that changes in the ratio of capital services to the wage bill and changes in the ICT share in total capital services are controlled for. Data on TFP are missing for Greece and South Korea, and on the ICT share, for Greece in the EUKLEMS data. Robust standard errors, two-way clustered by country and industry, in parentheses. Regressions are weighted by 1993 within-country employment shares.

Table P3: Further Outcomes—Hourly Wages

	$\Delta \ln$(mean hourly wage)			
	(1)	(2)	(3)	(4)
A. OLS				
Robot adoption	-0.010	0.057	0.042	0.039
	(0.026)	(0.013)	(0.016)	(0.017)
B. IV: replaceable hours				
Robot adoption	0.067	0.097	0.085	0.087
	(0.043)	(0.023)	(0.021)	(0.021)
F-statistic	41.8	33.9	30.4	34.8
C. IV: reaching & handling				
Robot adoption	0.075	0.142	0.119	0.118
	(0.058)	(0.032)	(0.031)	(0.031)
F-statistic	30.1	16.1	12.5	15.8
D. IV: replaceable hours, reaching & handling entered jointly				
Robot adoption	0.068	0.096	0.082	0.084
	(0.044)	(0.023)	(0.020)	(0.021)
F-statistic	25.4	17.4	15.8	18.0
J-statistic (*p*-value)	0.81	0.05	0.08	0.13
Country trends & controls		✓	✓	✓
Changes in skill mix			✓	✓
Changes in other capital				✓
Observations	238	238	238	224

Notes: Robot adoption refers to the percentile in the weighted distribution of changes in robot density, divided by one hundred. Controls include initial (1993) values of log wages and the ratio of capital services to the wage bill. "Changes in skill mix" indicates that changes in the hour shares of middle and high skill workers are controlled for. "Changes in other capital" indicates that changes in the ratio of capital services to the wage bill and changes in the ICT share in total capital services are controlled for. Data on the ICT share are missing for Greece in the EUKLEMS data. Robust standard errors, two-way clustered by country and industry, in parentheses. Regressions are weighted by 1993 within-country employment shares.

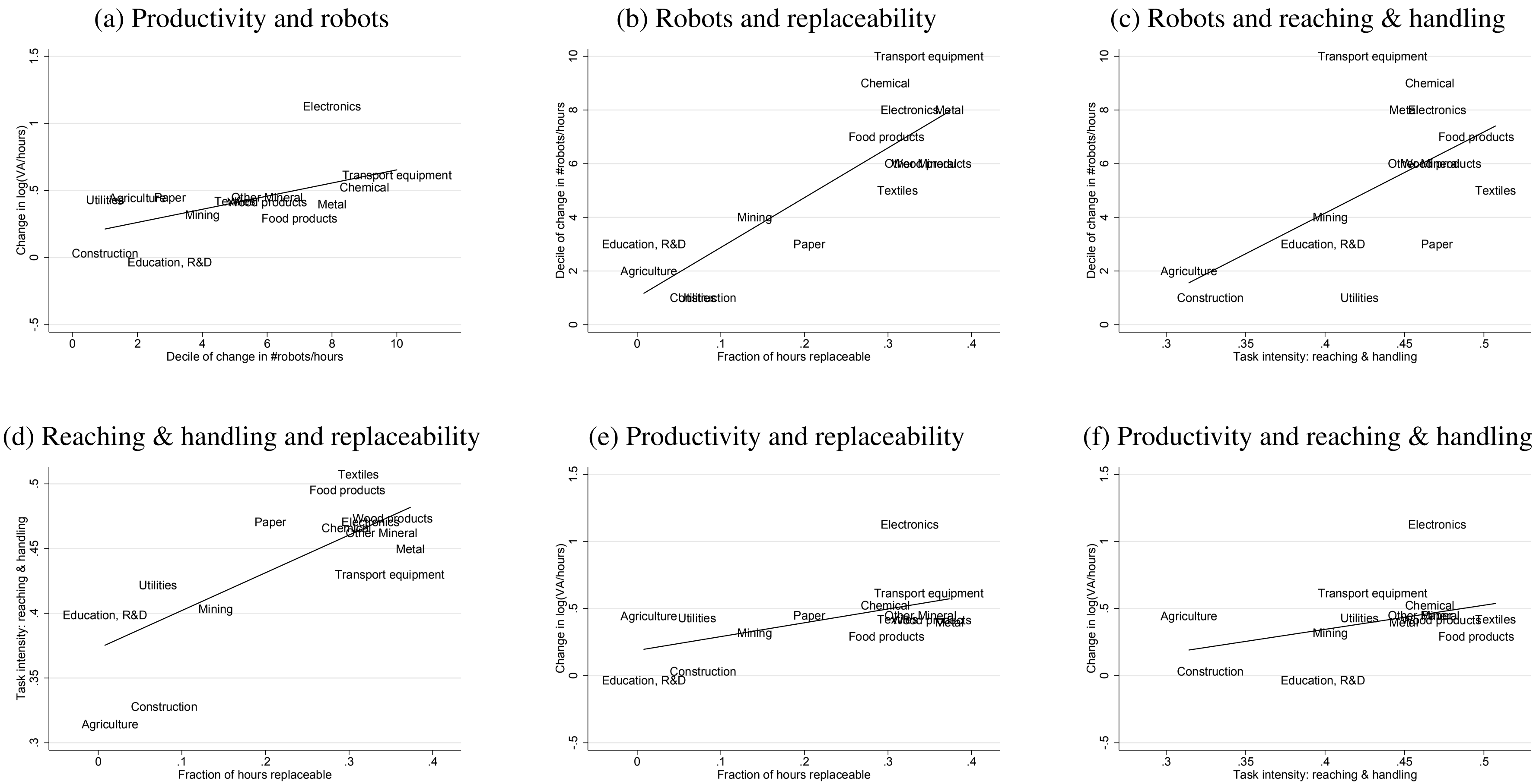
Table P4: Further Outcomes—Share in Hours Worked by Skill Group

		High			Middle			Low	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
A. OLS									
Robot adoption	1.22	1.94	1.64	2.18	3.85	4.07	-3.40	-5.79	-5.72
	(0.94)	(1.91)	(1.85)	(3.28)	(3.23)	(2.89)	(2.68)	(1.63)	(1.65)
B. IV: replaceable hours									
Robot adoption	2.29	1.81	1.22	4.34	8.21	7.37	-6.63	-10.0	-8.59
	(2.21)	(3.11)	(2.84)	(7.72)	(5.58)	(4.36)	(5.72)	(3.44)	(2.68)
F-statistic	41.8	33.9	36.8	41.8	33.9	36.8	41.8	33.9	36.8
C. IV: reaching & handling									
Robot adoption	6.50	7.14	5.95	-4.37	1.65	2.91	-2.14	-8.78	-8.87
	(2.12)	(3.40)	(3.09)	(4.22)	(4.83)	(4.21)	(3.90)	(3.38)	(3.56)
F-statistic	30.1	16.1	19.3	30.1	16.1	19.3	30.1	16.1	19.3
D. IV: replaceable hours, reaching & handling entered jointly									
Robot adoption	2.63	1.67	1.13	3.65	8.38	7.46	-6.27	-10.1	-8.58
	(2.13)	(3.10)	(2.84)	(7.38)	(5.61)	(4.36)	(5.52)	(3.45)	(2.67)
F-statistic	25.4	17.4	19.7	25.4	17.4	19.7	25.4	17.4	19.7
J-statistic (p-value)	0.12	0.11	0.10	0.20	0.17	0.15	0.32	0.57	0.88
Country trends & controls		✓	✓		✓	✓		✓	✓
Changes in other capital			✓			✓			✓
Observations	238	238	224	238	238	224	238	238	224

Notes: Robot adoption refers to the percentile in the weighted distribution of changes in robot density, divided by one hundred. Controls include initial (1993) values of log wages and the ratio of capital services to the wage bill. "Changes in other capital" indicates that changes in the ratio of capital services to the wage bill and changes in the ICT share in total capital services are controlled for. Data on the ICT share are missing for Greece in the EUKLEMS data. Robust standard errors, two-way clustered by country and industry, in parentheses. Regressions are weighted by 1993 within-country employment shares.

5 Appendix Figures and Tables

Figure A1: Cross-Industry Variation in Growth of Productivity, the Replaceability of Labor, and the Task Intensity of Reaching & Handling



(a) Productivity and robots

(b) Robots and replaceability

(c) Robots and reaching & handling

(d) Reaching & handling and replaceability

(e) Productivity and replaceability

(f) Productivity and reaching & handling

Table A1: List of All EUKLEMS Industries

Code	Included in Robotics data	Label	Code description
AtB	✓	Agriculture	Agriculture, hunting, forestry, and fishing
C	✓	Mining	Mining and quarrying
15t16	✓	Food products	Food products, beverages and tobacco
17t19	✓	Textiles	Textiles, textile products, leather and footwear
20	✓	Wood products	Wood and products of wood and cork
21t22	✓	Paper	Pulp, paper, paper products, printing and publishing
23t25	✓	Chemical	Chemical, rubber, plastics and fuel
26	✓	Other mineral	Other non-metallic mineral products
27t28	✓	Metal	Basic metals and fabricated metal products
29			Machinery, not elsewhere classified
30t33	✓	Electronics	Electrical and optical equipment
34t35	✓	Transport equipment	Transport equipment
36t37			Manufacturing not elsewhere classified; recycling
50			Sale, maintenance and repair of motor vehicles and motorcycles; retail sale of fuel
51			Wholesale trade and commission trade, except of motor vehicles and motorcycles
52			Retail trade, except of motor vehicles and motorcycles; repair of household goods
60t63			Transport and storage
64			Post and telecommunications
70			Real estate activities
71t74			Renting of machinery and equipment and other business activities
E	✓	Utilities	Electricity, gas, water supply
F	✓	Construction	Construction
H			Hotels and restaurants
J			Financial intermediation
L			Public administration, defence, and compulsory social security
M	✓	Education, R&D	Education
N			Health and social work
O			Other community, social and personal services

Notes: Industry M in the World Robotics data includes research and development in addition to education, whereas research and development are included in industry 71t74 in the EUKLEMS data.

Table A2: Summary Statistics by Country

A. 1993 Levels Averaged by Country

	#robots/H	ln(VA/H)	ln(VA)	ln(H)
Australia	0.07	3.30	9.56	6.26
Austria	0.63	3.09	8.64	5.55
Belgium	1.20	3.72	8.94	5.22
Denmark	0.42	3.52	8.41	4.89
Finland	0.68	3.15	8.29	5.14
France	0.79	3.37	10.63	7.26
Germany	1.71	3.38	11.00	7.63
Greece	0.00	2.53	8.76	6.23
Hungary	0.05	1.68	7.50	5.82
Ireland	0.00	3.26	8.05	4.79
Italy	1.13	3.17	10.54	7.37
Netherlands	0.25	3.60	9.35	5.75
South Korea	0.28	1.90	9.76	7.86
Spain	0.36	3.21	10.12	6.91
Sweden	1.39	3.21	8.69	5.47
United Kingdom	0.50	3.38	10.62	7.24
United States	0.41	3.39	12.27	8.88
Mean	0.58	3.11	9.48	6.37

B. Changes from 1993-2007 Averaged by Country

	#robots/H	ln(VA/H)	ln(VA)	ln(H)
Australia	0.12	0.22	0.34	0.12
Austria	0.61	0.51	0.32	-0.19
Belgium	1.23	0.29	0.20	-0.09
Denmark	1.57	0.19	0.17	-0.02
Finland	1.05	0.43	0.39	-0.04
France	1.20	0.29	0.14	-0.15
Germany	2.73	0.28	0.02	-0.26
Greece	0.03	0.16	0.04	-0.12
Hungary	0.08	0.56	0.37	-0.20
Ireland	0.10	0.44	0.65	0.20
Italy	1.39	0.17	0.10	-0.06
Netherlands	0.54	0.24	0.19	-0.05
South Korea	1.31	0.71	0.45	-0.26
Spain	1.21	0.13	0.31	0.18
Sweden	0.80	0.43	0.46	0.04
United Kingdom	0.34	0.26	0.14	-0.12
United States	0.97	0.27	0.28	0.01
Mean	0.90	0.33	0.27	-0.06

Notes: H stands for million hours worked. Value added (VA) is measured in millions of 2005 US$, converted from local currencies using 2005 nominal exchange rates where applicable. Country-level and overall means are weighted by each industry's 1993 share of hours within a country.

Table A3: Summary Statistics by Industry

A. 1993 Levels Averaged by Industry

	#robots/H	ln(VA/H)	ln(VA)	ln(H)
Agriculture	0.01	2.34	9.24	6.90
Chemical	1.16	3.72	9.40	5.68
Construction	0.01	3.30	10.26	6.96
Education, R&D	0.02	3.45	10.18	6.72
Electronics	0.95	2.78	8.38	5.60
Food products	0.34	3.35	9.32	5.97
Metal	2.37	3.23	9.09	5.86
Mining	0.07	4.27	8.22	3.95
Other Mineral	0.34	3.27	8.07	4.80
Paper	0.06	3.36	8.89	5.53
Textiles	0.12	2.79	8.34	5.55
Transport equipment	5.36	3.14	8.41	5.27
Utilities	0.00	4.30	9.13	4.83
Wood products	0.77	2.77	7.36	4.59

B. Changes from 1993-2007 Averaged by Industry

	#robots/H	ln(VA/H)	ln(VA)	ln(H)
Agriculture	0.03	0.44	0.11	-0.33
Chemical	3.33	0.52	0.47	-0.05
Construction	0.02	0.03	0.34	0.30
Education, R&D	0.06	-0.03	0.19	0.22
Electronics	1.32	1.13	1.13	0.00
Food products	1.21	0.29	0.16	-0.14
Metal	1.67	0.40	0.45	0.06
Mining	0.29	0.32	0.00	-0.32
Other Mineral	0.81	0.45	0.34	-0.11
Paper	0.14	0.45	0.31	-0.14
Textiles	0.30	0.42	-0.35	-0.77
Transport equipment	8.07	0.61	0.64	0.02
Utilities	0.02	0.43	0.28	-0.15
Wood products	0.84	0.41	0.36	-0.05

Notes: H stands for million hours worked. Value added (VA) is measured in millions of 2005 US$, converted from local currencies using 2005 nominal exchange rates where applicable. Means are not weighted.

Table A4: Summary Statistics for Robots Variables

A. 1993 Levels

	Mean	Stdev	Min	Median	Max
#robots/hours	0.582	1.773	0.000	0.004	15.697
$\ln(1+\#\text{robots/hours})$	0.245	0.514	0.000	0.004	2.815
$1,000 \times$ robot services/wage bill	0.346	1.006	0.000	0.004	10.287

B. Changes from 1993-2007

	Mean	Stdev	Min	Median	Max	Mean 1st qrtl	Mean 2nd qrtl	Mean 3rd qrtl	Mean 4th qrtl
Δ(#robots/hours)	0.898	2.795	-2.617	0.024	28.028	-0.018	0.012	0.130	3.479
$\Delta\ln(1+\#\text{robots/hours})$	0.199	0.341	-0.697	0.024	1.806	-0.007	0.012	0.103	0.700
$\Delta(1,000 \times$ robot services/wage bill)	0.110	0.641	-3.298	0.004	5.069	-0.163	0.002	0.016	0.635

Notes: The variable 'hours' refers to million hours worked. The number of robots was computed from annual investment data using the perpetual inventory method and assuming a depreciation rate of ten percent. The initial value was taken from the World Robotics database. Robot services equal 0.15 times the price of robots, times the number of robots. The adjustment factor of 0.15 reflects depreciation at ten percent and an interest rate of five percent. The price of robots is the average unit price of robots in the US in the relevant year, expressed in 2005 US$. Reported statistics are weighted by each industry's 1993 share of hours within a country.

Table A5: Changes in Robots Input and Growth in Productivity 1993-2007—Alternative Functional Forms

	$\Delta\ln$(VA/H)			
	(1)	(2)	(3)	(4)
A. Change in robot density, #Robots/Hours				
OLS	0.029	0.032	0.037	0.036
	(0.017)	(0.016)	(0.015)	(0.015)
IV: replaceable hours	0.146	0.151	0.168	0.172
	(0.092)	(0.091)	(0.078)	(0.080)
F-statistic	5.8	5.7	5.4	5.5
B. Change in $\ln(1+\#\text{Robots}/\text{Hours})$				
OLS	0.348	0.406	0.446	0.453
	(0.189)	(0.184)	(0.164)	(0.163)
IV: replaceable hours	0.794	0.808	0.908	0.937
	(0.425)	(0.413)	(0.342)	(0.342)
F-statistic	22.8	20.8	19.2	20.5
C. Change in $1{,}000\times(\text{Robot services})/(\text{Wage bill})$				
OLS	0.121	0.116	0.117	0.121
	(0.079)	(0.064)	(0.056)	(0.058)
IV: replaceable hours	1.414	1.445	1.817	1.888
	(1.111)	(1.166)	(1.483)	(1.526)
F-statistic	1.8	1.7	1.2	1.2
Country trends		✓	✓	✓
Controls			✓	✓
Changes in other capital				✓
Observations	238	238	238	224

Notes: Controls include initial (1993) values of log wages and the ratio of capital services to the wage bill. “Changes in other capital” indicates that changes in the ratio of capital services to the wage bill and changes in the ICT share in total capital services are controlled for. Data on the ICT share are missing for Greece in the EUKLEMS data. Robust standard errors, two-way clustered by country and industry, in parentheses. Regressions are weighted by 1993 within-country employment shares.

Table A6: Falsification Tests for Instrumental Variables

	Replaceable hours	Reaching & handling
	(1)	(2)
	$\Delta\ln(\text{VA/H})$	$\Delta\ln(\text{VA/H})$
A. Growth in outcome 1993-2007 (benchmark)		
Instrumental variable	1.13	1.54
	(0.58)	(1.19)
Observations	238	238
B. Growth in outcome 1993-2007, non-adopters (1993)		
Instrumental variable	0.85	0.41
	(0.90)	(1.57)
Observations	76	76
C. Growth in outcome 1993-2007, non-adopters (2007)		
Instrumental variable	-0.37	0.01
	(0.72)	(1.84)
Observations	27	27
D. Growth in outcome 1979-1993		
Instrumental variable	0.44	0.15
	(0.60)	(1.18)
Observations	224	224
E. Growth in outcome 1979-1993, non-adopters (1993)		
Instrumental variable	-0.11	-1.06
	(0.81)	(1.58)
Observations	72	72
p-value of test for equality, A versus B	0.65	0.33
p-value of test for equality, A versus C	0.04	0.36
p-value of test for equality, A versus D	0.00	0.00
p-value of test for equality, A versus E	0.01	0.02

Notes: Results from OLS regressions are shown. All regressions control for country trends. Robust standard errors, two-way clustered by country and industry, in parentheses. Regressions are weighted by 1993 within-country employment shares. Panel *A* shows reduced forms for the full sample. Panel *B* shows reduced forms for country-industry cells that had zero robots in 1993 (non-adopters in 1993), while Panel *C* does the same for country-industry cells that did not use any robots in 1993 or 2007 (non-adopters in 2007). In Panel *D*, the outcomes are changes in the variables from 1979-1993, and the same in Panel *E*, but restricting the sample to country-industries that had not adopted robots by 1993. Data on productivity growth prior to 1993 are missing for Hungary. Tests for equality of coefficients are based on seemingly unrelated regressions.

Table A7: Changes in Robots Input and Growth in Productivity 1993-2007—Controlling for Other Task Measures

	OLS				IV			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Robot adoption	0.64	0.66	0.40	0.34	0.99	1.05	0.81	0.72
	(0.22)	(0.24)	(0.14)	(0.13)	(0.39)	(0.38)	(0.32)	(0.28)
ΔK		0.10		0.11		0.10		0.11
		(0.08)		(0.07)		(0.07)		(0.06)
$\Delta(K_{ICT}/K)$		-0.02		-0.03		-0.05		-0.02
		(0.20)		(0.11)		(0.18)		(0.10)
Abstract			0.25	0.24			0.26	0.24
			(0.08)	(0.08)			(0.08)	(0.08)
Routine			0.23	0.23			0.20	0.20
			(0.08)	(0.08)			(0.08)	(0.08)
Manual			-0.07	-0.06			0.01	-0.00
			(0.04)	(0.04)			(0.04)	(0.03)
Offshoreability			0.16	0.18			0.17	0.18
			(0.04)	(0.05)			(0.03)	(0.04)
F-statistic					33.9	36.8	21.0	24.2
Observations	238	224	238	224	238	224	238	224

Notes: This table reports the same specifications as in columns (3) and (4) of Panels A and B in Table 1, but this time reporting the coefficients on capital intensity and ICT. It then adds controls for task measures and offshoreability. Robot adoption refers to the percentile in the weighted distribution of changes in robot density, divided by one hundred. All regressions control for country trends, as well as initial (1993) values of log wages and the ratio of capital services to the wage bill. ΔK denotes the change in the ratio of capital services to the wage bill and $\Delta(K_{ICT}/K)$ denotes the change in the ICT share in total capital services. Data on the ICT share are missing for Greece in the EUKLEMS data. The task variables Abstract, Routine, Manual, and Offshoreability are from Autor and Dorn (2013). We aggregated these variables to the industry level using the 1980 US census, and standardized them to have zero mean and unit variance within our estimation sample. Robust standard errors, two-way clustered by country and industry, in parentheses. Regressions are weighted by 1993 within-country employment shares.

Table A8: Changes in Robots Input and Growth in Productivity 1993-2007—OLS & IV Estimates, Further Robustness Checks

	(1)	(2)	(3)	(4)	(5)	(6)
A. OLS						
Robot adoption	0.64	0.56	0.48	0.35	0.32	0.26
	(0.22)	(0.20)	(0.16)	(0.17)	(0.17)	(0.17)
B. IV: replaceable hours						
Robot adoption	0.99	0.96	0.84			
	(0.39)	(0.42)	(0.39)			
F-statistic	33.9	30.4	22.5			
C. IV: reaching & handling						
Robot adoption	0.90	0.72	0.50			
	(0.45)	(0.41)	(0.38)			
F-statistic	16.1	12.5	10.0			
D. IV: replaceable hours, reaching & handling entered jointly						
Robot adoption	0.99	0.98	0.88			
	(0.39)	(0.43)	(0.40)			
F-statistic	17.4	15.8	11.4			
J-statistic (*p*-value)	0.66	0.34	0.24			
Country trends & controls	✓	✓	✓	✓	✓	✓
Changes in skill mix		✓	✓		✓	✓
Changes in log wage			✓		✓	✓
Industry trends				✓	✓	✓
Changes in other capital						✓
Observations	238	238	238	238	238	224

Notes: Robot adoption refers to the percentile in the weighted distribution of changes in robot density, divided by one hundred. Controls include initial (1993) values of log wages and the ratio of capital services to the wage bill. "Changes in skill mix" indicates that changes in the hour shares of middle and high skill workers are controlled for. "Changes in other capital" indicates that changes in the ratio of capital services to the wage bill and changes in the ICT share in total capital services are controlled for. Data on the ICT share are missing for Greece in the EUKLEMS data. Robust standard errors, two-way clustered by country and industry, in parentheses. Regressions are weighted by 1993 within-country employment shares.

Table A9: Changes in Robots Input and Growth in Value Added and Hours 1993-2007—OLS & IV Estimates

	$\Delta \ln(VA)$				$\Delta \ln(H)$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. OLS								
Robot adoption	0.34	0.60	0.51	0.49	-0.02	0.03	-0.14	-0.18
	(0.18)	(0.23)	(0.21)	(0.22)	(0.23)	(0.25)	(0.17)	(0.17)
B. IV: replaceable hours								
Robot adoption	0.57	0.64	0.55	0.58	-0.30	-0.28	-0.44	-0.47
	(0.37)	(0.40)	(0.42)	(0.39)	(0.53)	(0.52)	(0.33)	(0.31)
F-statistic	41.8	34.2	33.9	36.8	41.8	34.2	33.9	36.8
C. IV: reaching & handling								
Robot adoption	0.27	0.31	-0.01	0.14	-0.42	-0.40	-0.90	-0.88
	(0.50)	(0.53)	(0.56)	(0.48)	(0.79)	(0.76)	(0.58)	(0.48)
F-statistic	30.1	25.0	16.1	19.3	30.1	25.0	16.1	19.3
D. IV: replaceable hours, reaching & handling entered jointly								
Robot adoption	0.55	0.60	0.57	0.59	-0.31	-0.29	-0.43	-0.46
	(0.38)	(0.41)	(0.41)	(0.39)	(0.55)	(0.54)	(0.32)	(0.31)
F-statistic	25.4	19.3	17.4	19.7	25.4	19.3	17.4	19.7
J-statistic (*p*-value)	0.08	0.10	0.08	0.07	0.76	0.73	0.19	0.14
Country trends		✓	✓	✓		✓	✓	✓
Controls			✓	✓			✓	✓
Changes in other capital				✓				✓
Observations	238	238	238	224	238	238	238	224

Notes: Robot adoption refers to the percentile in the weighted distribution of changes in robot density, divided by one hundred. Controls include initial (1993) values of log wages and the ratio of capital services to the wage bill. "Changes in other capital" indicates that changes in the ratio of capital services to the wage bill and changes in the ICT share in total capital services are controlled for. Data on the ICT share are missing for Greece in the EUKLEMS data. Robust standard errors, two-way clustered by country and industry, in parentheses. Regressions are weighted by 1993 within-country employment shares.

Table A10: Percentage Losses in 2007 Value Added per Hour for the Counterfactual Scenario of No Increase in Robots

	Robot-using industries	All industries
Australia	8.0	2.8
Austria	18.9	6.5
Belgium	19.2	5.7
Denmark	20.3	5.9
Finland	20.1	7.6
France	17.1	4.4
Germany	22.8	6.9
Greece	11.1	3.3
Hungary	7.1	2.6
Ireland	9.9	4.1
Italy	16.0	4.8
Netherlands	13.7	3.8
South Korea	17.6	8.3
Spain	17.6	6.1
Sweden	16.9	5.2
United Kingdom	16.9	4.7
United States	13.5	3.5
Mean	15.7	5.1

Notes: The percentage loss in $y \equiv$ VA/H is given by $100 \times (1 - y^{cf}_{c,2007}/y_{c,2007})$. See the text for details of how the counterfactual outcome $y^{cf}_{c,2007}$ was calculated. The figures for the entire economy were obtained by multiplying the numbers reported in the first four columns by the share in value added of the robots-using industries in a given country in 2007. This amounts to assuming that no robots were used in the industries not included in our sample. In fact, the average share of the excluded industries ("all other manufacturing" and "all other non-manufacturing") in total robots deliveries across countries in 2007 was 0.6 percent.

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