Machines and machinists: Capital–skill complementarity from an international trade perspective*

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Abstract

We estimate the effect of imported machines on the wages of machine operators utilizing Hungarian linked employer-employee data. We infer exposure to imported machines from detailed trade statistics of the firm and the occupation description of the worker. We find that workers exposed to imported machines earn about 8 percent higher wages than other machine operators at the same firm. When we proxy for unobserved worker characteristics, we find a significant 3 percent wage premium, suggesting that the relationship is causal. The return to schooling is also higher on imported machines. We build a simple matching model consistent with these findings. Our findings suggest that machine imports can be an important channel through which skill-biased technical change reaches less developed and emerging economies.

Introduction

The vast majority of machinery production is concentrated in a handful of advanced economies. As a consequence, most other countries rely heavily on machinery imports (Eaton and Kortum 2001, Caselli and Wilson 2004). Imported machines have a wide ranging impact on the economy. They contribute to capital accumulation and growth (De Long and Summers 1991, Alfaro and Hammel 2007) and they can be a source of R&D spillovers (Coe and Helpman 1995, Keller 2004). In this paper we argue that they also increase the demand for skilled labor.

Our starting point is that machines produced in advanced economies are more sophisticated and of a higher quality than those produced in a less developed country. Most Indian users find computer numerically controlled (CNC) machine tools imported from Japan and Taiwan to be more reliable, more accurate and more productive than similar Indian machines (Sutton 2000).

Sophisticated machines, in turn, require highly trained, skillful and attentive operators. Operating CNC lathes, for example, requires more training than operating traditional lathes.[1] More broadly, computerization has increased the demand for complex skills (Autor, Levy and Murnane 2003), even within the same occupation (Spitz-Oener 2006).[2] In other words, the technology embodied in up-to-date sophisticated machines is skill biased. Taken together, we argue that importing machines from advanced economies amounts to importing skill-biased technical change.

We estimate how imported machines have shaped the wages of machine operators in Hungary between 1994 and 2004. We infer exposure to imported machines from detailed trade statistics of the firm and the occupation description of the worker. We find that workers exposed to imported machines earn about 8 percent higher wages than other machine operators at the same firm. This suggests that imported capital and worker skill are complementary.

The period of our study was characterized by rapid trade liberalization, especially with respect to the European Union which Hungary joined in 2004.[3] Liber-

[1]Around a quarter of the lessons associated with CNC lathing offered at toolingu.com are directly associated with CNC programming.

[2]Our paper is related to the vast literature on computerization and skill-biased technical change, surveyed in Katz and Autor (1999) and Acemoglu (2002). The key difference is that we study wages and technology choice within a narrow occupation and not the broad trends in inequality.

[3]The free trade agreement between the European Community and Hungary reduced tariffs substantially. The average tariff on machinery imports was 10 percent in 1992 and below 1 percent in 1997. Tariffs had been completely phased out by 2001.

alization coincided with a surge in machine imports. There was a gradual increase in machine imports during the 1980s, which accelerated sharply in the first half of the 1990s. By 1995, an overwhelming majority of machinery was coming from imports.

We use linked employer-employee data on a six-percent representative sample of Hungarian machine operators. We link each operator to the import flows of her employer. For each firm, Customs Statistics record all the import transactions between 1992 and 2003, their precise product classification and country of origin. We can thus distinguish machine operators who work at a firm using only domestic machines from those who work at a firm that has recently purchased an imported machine. Moreover, the product classification allows us to select the machines that are most relevant for the operator's occupation. For example, "printing machine operators" are linked with "offset printing machinery," but not with "metal lathes."

Our findings show that workers at firms that import their specific machinery earn 10.5 percent more than workers with no access to imported machinery of their specific occupation. Some of this wage differential may be due to omitted firm characteristics. Importing firms may be more productive, better managed, and may be able to attract a better workforce. When we contrast operators (e.g., printing machine operators) working at firms that import *their specific* machines (e.g., offset printing machine) machines to those working at firms that import machines *unrelated to their occupation* (e.g., metal lathes), we find a wage gap of 8.2 percent. This is our preferred estimate of the effect of imported machinery on wages.

The difference in wages reflects differences in skill as well as differences in the *returns to skill*. Among workers operating domestic machines, the wage gap between those with completed high school and those with primary schooling is 6.9 percent. Among those working on imported machines, the return to a secondary degree is 11.3 percent. This suggests that imported machines increase the returns to skill substantially. However, much of the skills of machine operators are *unobservable* and are only partially explained by formal schooling. This is important, because imported machines are operated by better skilled workers than domestic ones, and hence our estimated wage differential is the combined effect of increased returns to skill and unobserved skill differences.[4]

In order to differentiate the causal effect of imported machines from unobserved heterogeneity in worker skill, we pursue a fixed effects strategy. In our data, the same individuals are sampled in multiple waves, but cannot be linked over time.

[4]See DiNardo and Pischke (1997) and Entorf, Gollac and Kramarz (1999) in the context of the wage effects of computers estimated by Krueger (1993).

Nonetheless, the sampling design permits us to construct a pseudo-panel of workers, in which we group workers based on a number of observable characteristics. We find that the wages of the worker *increase* by about 3 percent after she receives a related imported machine.

The richness of the import data permits us to explore the sources of the wage effect in more detail. In particular, we can ask if imports from countries on the technology frontier matter more. We select 10 OECD countries in which R&D expenditures in the machinery sector have exceeded 3.8 percent of value added.[5] We find that it is *only* these imports that matter; imports from other countries have no significant effect on wages. This reinforces the interpretation that the machines embody sophisticated, skill biased technology.

What lies behind these wage patterns? We build a simple matching model along the lines of Roy (1951), Jovanovic (1998), and Yeaple (2005) to provide an answer. Workers are heterogeneous in (unobserved) human capital, while machines are heterogeneous in their quality. Imported machines, in particular, are higher quality than domestic ones, but they are also more expensive. There is a fixed supply of workers who are hired in an efficient labor market. Machine quality and worker human capital are supermodular in the production function: the returns to skill are higher on higher-quality machines. This immediately gives rise to a strong sorting result: workers above a certain threshold of skill all work on imported machines, while those below work on domestic machines.

We conduct a simple trade liberalization experiment within the model by reducing the relative price of imported machines. In response, a bigger set of firms begins importing. These new importers are better than non-importers, but worse than continuous importers. Workers at these firms enjoy a discrete jump in their wages in response to their increased marginal product. Interestingly, continuous importers also enjoy wage increases due to general equilibrium effects. Because imported machines are now cheaper, if skilled wages remained the same, new entrants could make a profit by buying an imported machine and hiring a skilled worker. Competition for skilled workers increases their wage, even if in equilibrium their employer does not upgrade their machines.

The model is consistent with both the cross-section and the time-series evidence on wages. Workers on imported machines earn more than those on domestic machines. They also enjoy a higher return to their skill. Workers whose employer has just started to import receive a discrete jump in their wages. As predicted by

[5]The countries are Sweden, Norway, Japan, Belgium, South Korea, Finland, Germany, Denmark, USA, and the UK. We use the OECD R&D statistics reported in Table 2 of Acharya and Keller (2009).

the model, a lot of importing firms in a worker's sector raise the worker's wage if they already import, but not if they still use a domestic machine.

The model also makes predictions about the *timing* of imports. Firms with the best workers start importing first. The productivity of their skilled operators makes it profitable for them to buy the better machine even when tariffs are high. As tariffs continue to fall, the threshold of importers keeps falling and firms with a poorer and poorer pool of workers start importing. This prediction is also borne out by the data. We distinguish early importers as those workers who were among the first 50 percent of workers to receive imported machines. If we rank workers by their wages, early importers are at the top of the distribution, while late importers are at the bottom of the distribution.

To the best of our knowledge, this is the first paper to provide micro evidence on how imported technology changes the demand for skill. In parallel work, Parro (2010) develops a quantitative model of trade to show that trade in capital goods, together with capital-skill complementarity can explain a large fraction of the increase in the skill premium worldwide. The main difference between his work and ours is that he uses aggregate data (capital goods vs other goods) to quantify the role of "skill-biased trade," whereas we provide more direct micro-level evidence.

Our work is also related to several studies that show that technology transfers are embodied in imports. Coe and Helpman (1995) show that countries importing from high-R&D partners have high productivity. Acharya and Keller (2009) find similar results at the industry level. Halpern, Koren and Szeidl (2010) show that firms importing their intermediate inputs are more productive, partly because these inputs are of a higher quality.

Understanding machine imports as a source of technology transfer can shed light on why wage and income inequality has increased tremendously in developing countries, and why these increases have mostly coincided with periods of trade liberalization (see Goldberg and Pavcnik (2007), for a survey). Most researchers point to skill-biased technical change (SBTC) as an explanation. Given, however, that most skill-biased technologies are developed in advanced economies, the liberalization of capital imports is a necessary condition for SBTC to reach developing countries. Consistent with this reasoning, Alfaro and Hammel (2007) show that (capital account) liberalization in emerging economies was followed by a surge in capital imports.

Other papers have also explored links between between technology choice and trade liberalization. Costantini and Melitz (2008) and Yeaple (2005) build models in which technology choice and trading status are correlated: exporting firms are more likely to use advanced technologies. Verhoogen (2008) finds that Mexican exporters upgraded both their technology and the skill of their workforce after the 1994 devaluation of the peso, because better skilled workers are required to produce the high quality goods that are in demand in export markets. Bustos (2011) finds that the MERCOSUR trade agreement has led Argentine firms to export more and, concurrently, to upgrade their technology. She builds a model in which export expansion helps firms overcome the fixed costs of technology adoption. All these papers link technology upgrading to the *export decisions* of firms. Our model relates it to *imported* capital goods. The key differences are that (i) imports are subject to the domestic trade policies, so even unilateral liberalizations can lead to SBTC, and that, (ii) in developing countries, the use of imported machinery can affect a larger set of workers than technology upgrading by exporters.

More broadly, our findings that machine quality and worker skills are complementary lend support to the view that complementarities are an important feature of the development process (see Kremer (1993), and Jones (2011)). If skilled workers are required to operate new, more advanced technologies, then the lack of adequate education and training is a barrier to the spillover of technologies. Moreover, if labor market institutions do not facilitate the efficient matching of workers with machines, aggregate productivity will be substantially lower (see Bénabou (1996)). Both effects make it harder for poor countries to catch up with the productivity frontier, magnifying differences in income per capita.

The paper is organized as follows. The first Section introduces the data set and provides some descriptive statistics. Section 2 examines how machine operator wages are affected by machine imports. Section 3 introduces a simple model of worker–machine assignment that is consistent with the uncovered empirical regularities. The model has additional implications about the effects of trade liberalization which are then taken to the data. Section 4 offer discusses extensions of the empirical exercise, and Section 5 concludes.

1 Data

We use linked employer-employee data. Employee data come from the Hungarian Structure of Earnings Survey (*Bértarifa*), which contains a 6 percent quasi-random sample of all employees (10 percent for white-collar workers), recording their earnings, 4-digit occupation, education, age and gender. We use the annual waves between 1994 and 2004, and limit our sample to 64 machine operating occupations (excluding vehicle drivers, see Table A.1 in the Appendix), resulting in about 20,000 employees per year.

In our benchmark specification, we limit the sample to firms that have at least 50 employees, because the sampling procedure of *Bértarifa* is somewhat different for smaller firms. Results are virtually unchanged if we include all firms. We drop all part-time employees and those earning less than the minimum wage. We also drop firm-occupation-year cells in which there are more than 20 employees because we are likely to measure the import exposure of these workers with high error (see below). Again, results are not sensitive to these adjustments. Our final sample includes 8–10,000 employees per year (see Table 1).

Each employer is matched to its Customs Statistics (CS) record based on a unique firm identifier. The CS contains the universe of trading firms, recording their exports and imports in 6-digit Harmonized System product breakdown for all years from 1992 to 2003. For each worker in *Bértarifa*, we can precisely identify the international transactions of his/her employer. In particular, not only do we see whether the employer imported any machinery in the past, we also see the specific equipment goods that it imported. We restrict our attention to 260 specialized machines and instruments that can be associated with a particular industry and occupation.[6] We exclude general purpose machines (e.g., computers) and tools (e.g., screwdrivers) because they can be used by a wide range of workers, not only machine operators. Around one third of all imports of machinery, vehicles and instruments is spent on such specialized machines.

We match the 4-digit occupation codes (FEOR) to the 6-digit product codes (HS) to identify machines and their operators. For example, FEOR code 8127 covers "Printing machine operators." This code is matched with "Photo-typesetting and composing machines" (HS code 844210), as well as with "Reel fed offset printing machinery" (844311), but not with "Machines for weaving fabric, width < 30 cm" (844610). Note that this is a many-to-many match: the average occupation is associated with 5.5 machines, and the average machine is associated with 1.3 occupations. The Appendix provides the details of this matching procedure, and Table A3 lists several examples of these matches. For each occupation o let μ_o denote the set of products that are matched.

For each worker in each year, we create a measure of access to imported machinery, which takes the value of one if the employer imported machine(s) specific to the worker's occupation any time in the past, and zero otherwise.[7] More formally, let M_{flt} denote the amount of imports of product l by firm f in year t. Then we

[6] Table A2 in the Appendix lists these machines.

[7] This assumes that machines do not depreciate. We also experimented with a 5-year lifetime for imported machines as well as a 10 percent annual depreciation. Results were very similar.

can define S_{fot}, the import exposure of occupation o at firm f in year t as follows:

$$S_{fot} = \begin{cases} 1 & \text{if } \max_{s \leq t, l \in \mu_o} M_{fls} > \bar{w}_s, \\ 0 & \text{otherwise.} \end{cases} \tag{1}$$

This index will take the value one if any of the products related to occupation o had imports higher than the average wage $\bar{w}_s$ in any year s prior to (and including) year t. We only count imports that are of higher value than the average wage to capture the purchase of a big piece of machinery that may affect wage setting at the firm. (Sometimes parts of the machine are classified within the same 6-digit product code.) If we include all positive imports, the results are similar.

Similarly, we define the import exposure of the *firm* as a dummy for having imported a machine in the past, irrespective of its type,

$$G_{ft} = \begin{cases} 1 & \text{if } \max_{s \leq t} M_{fls} > \bar{w}_t, \\ 0 & \text{otherwise.} \end{cases} \tag{2}$$

Clearly, $G_{ft} = \max_o S_{fot}$, that is, if any occupation is exposed to imports at the firm, the firm as a whole is also exposed.

Our identification strategy makes use of the fact that, for some workers, $S_{fot} \neq G_{ft}$. These are workers whose firm has imported a machine, but one that is not related to their occupation. These workers will serve as a control group for workers at the same firm in related occupations (see Section 2).

Table 1 reports the number of workers in each treatment category. The employer of around one third of the workers never imports any machinery during the sample period. Around one quarter works in a firm that has imported, but not their related machine. The remainder is exposed to imports of their related machine. The majority of imports come from high-R&D countries.

There are two potential sources of error with the measure S_{fot}. First, if some firms import capital indirectly, then we will classify some importers as nonimporters. This issue is not very severe for specialized machines, for which only 22 percent of the total imports was purchased by intermediary firms (wholesalers and retailers) in 1999, and the rest went directly to manufacturers.

Second, we do not know *which worker* within the specific occupation received the machine. If there are multiple machine operators in the same occupation at the same firm and only one of them is assigned the machine, we will wrongly classify the others as importers. This measurement error is more severe in large firms. We hence restricted the sample to firm–occupation–year cells which contain 20 workers or less.[8]

[8] In alternative specifications (not reported), we restricted the sample to firms and occupations of which there is only one worker in the sample. The results are indeed stronger in this case.

Table 1: Number of workers in each treatment category

Year	Did not import machine	Imported unrelated machine	Spec. machine outside top10	Spec. machine from top 10	Total
1994	3,420	2,519	688	1,717	8,344
1995	2,952	2,759	768	2,240	8,719
1996	2,701	2,573	797	2,283	8,354
1997	2,187	2,242	652	2,393	7,474
1998	2,486	2,457	795	2,651	8,389
1999	2,435	2,288	707	2,907	8,337
2000	2,736	2,495	801	3,075	9,107
2001	2,711	2,391	845	3,155	9,102
2002	3,245	2,692	770	3,246	9,953
2003	3,163	2,622	765	3,350	9,900
2004	3,871	2,792	762	3,482	10,907

Both measurement errors lead to an attenuation bias, hence our estimates of the wage effect can be understood as a *lower bound*. For expositional clarity, we refer to workers at a firm importing their specific machinery as "working on imported machines," and all other workers as "working on domestic machines," but the reader should bear in mind these caveats.

1.1 Variables and descriptive statistics

We are primarily interested in the wage effect of imported machines. Wages are measured as regular monthly earnings in the month of May, plus 1/12 of the overtime and other bonuses paid in the previous year. (Results are similar if we omit bonuses.)

We have categorical indicators for schooling, recording whether the worker has complete or incomplete primary, secondary, or tertiary education. Secondary degrees are further divided into vocational training (a mostly 3-year program providing practical training for skilled occupations) and the academic track (a 4- or 5-year program making one eligible for college admission).

We also record firm characteristics that likely affect wage setting. *Bértarifa* reports the total employment of the firm, and whether or not it is foreign owned. Both size (Oi and Idson 1999) and foreign ownership (Aitken, Harrison and Lipsey

1996, Brown, Earle and Telegdy 2010) are known to be positively correlated with wages.

Table 2 provides some descriptive statistics about the main variables used in the analysis. Around three quarters of our sample are male. Around two thirds of the workers have completed (some form of) high school, the rest have primary schooling or are high school dropouts. Slightly more than a quarter of the workers are employed by foreign-owned firms.

The table also reports the characteristics separately for importers and non-importers. Importers are more likely to be female, younger, more educated, earn higher wages, work at larger firms, and are more likely to work at a foreign firm. In other words, importing firms are "special" and have a special workforce (Bernard, Jensen and Schott 2009, Halpern et al. 2010). It will hence be important to control for firm characteristics in the wage regressions.

Table 2: Descriptive statistics of main variables

	Mean	Standard deviation	Mean of importers	Mean of nonimporters	t-test of equality
Gender (1 if male)	0.720		0.635	0.776	-47.03
Age (years)	39.443	10.571	38.366	40.143	-25.92
Education (1 if finished high school)	0.619		0.632	0.611	6.51
Monthly earning, log	10.951	0.626	11.107	10.849	64.59
Firm total employment, log	4.962	1.782	5.623	4.533	97.68
Firm is foreign owned	0.286		0.461	0.172	97.86

1.2 Pseudo-panel

Bértarifa does not provide an individual identifier, so we cannot link workers over time. However, sampling is based on the date of birth, those born on the 5th and 15th of the month are included in all waves (National Employment Service 2009). This ensures that subsequent waves track mostly the same set of workers. We exploit this feature of the data to construct a pseudo-panel.

We identify workers within the firm based on several observables: year of birth, gender, occupation, and educational attainment. We create cells based on these observables, and follow these cells over time. Table 3 reports some basic statistics about these cells. More than 95 percent of the 51,322 cells are unique: they contain only one worker. Of these, 16,355 cells can be followed over time, as they have observation in more than one year. These cells likely contain the same worker in all the years. We can then identify from the time-series variation within these cells. We use the cells with four or more years of data (in bold) in the fixed-effects estimation. There are 5,890 of these cells, covering 32,549 cell-year observations.

Table 3: Number of years and number of workers by cell

Number of years	Single-worker cells	Multi-worker cells	Total
1	32,897	1,329	34,226
2	6,937	286	7,223
3	3,528	138	3,666
4	**2,100**	96	2,196
5	**1,283**	59	1,342
6	**910**	47	957
7	**634**	44	678
8	**486**	22	508
9	**292**	31	323
10	**169**	15	184
11	**16**	3	19
Total	49,252	2,070	51,322

2 Estimating the Wage Differential

We estimate the effect of imported capital on wages in the following regression equation:

$$w_{ifot} = \alpha S_{fot} + \beta G_{ft} + \gamma X_{ft} + \delta Z_{it} + \nu_{ot} + u_{ifot} \tag{3}$$

Log monthly earnings of worker i in year t, w_{it}, depend on exposure to occupation-specific machine imports S_{fot}, exposure to firm-level imports G_{ft}, a vector of firm controls X_{ft}, a vector of individual controls Z_{it}, occupation-specific time fixed effects ν_{ot}, and an error term u_{ifot}. The index f denotes the firm of worker i at time t, similarly, o denotes her occupation.

The total effect of machine imports on wages is $\alpha + \beta$. This includes the occupation-specific and the firm-specific effects. The coefficient β captures the wage premium of *unrelated* machine operators at importing firms, relative to non-importing firms. As importers and non-importers may have unobserved differences, β may be nonzero even if there are no causal effects of imports on wages. For example, better educated managers may pay higher wages and be more likely to import at the same time. Selection on such firm unobservables is captured by

β.[9] We are therefore interested in the *differential* effect on wages of related and unrelated occupations within the firm. This is captured by α. Such a differential effect across occupations suggests that the link between wages and imports is technological.

Table 4: Imported machines and wages: pooled cross sections

	(1)	(2)	(3)	(4)
	Log monthly earnings			
Imported machine specific to occupation	0.105***	0.082***	0.053***	0.040***
	(0.006)	(0.007)	(0.009)	(0.010)
Imported some machine		0.055***		-0.006
		(0.007)		(0.009)
From high-R&D country:				
Imported machine specific to occupation			0.072***	0.041***
			(0.009)	(0.010)
Imported some machine				0.094***
				(0.009)
Firm employment (log)	0.071***	0.066***	0.069***	0.061***
	(0.003)	(0.003)	(0.003)	(0.003)
Firm has majority foreign owner	0.233***	0.227***	0.229***	0.219***
	(0.007)	(0.007)	(0.007)	(0.007)
Individual controls	YES	YES	YES	YES
Occupation*year fixed effects	YES	YES	YES	YES
Observations	98,225	98,225	98,225	98,225
R-squared	0.413	0.415	0.415	0.419

Notes: All regressions control for gender, a dummy for completed high school, age, age squared, and occupation*year fixed effects (coefficients not reported). Standard errors (in parantheses) are clustered by firm*year. *** p<0.01, ** p<0.05, * p<0.1 See text for sample definition and other details.

The results are reported in Table 4. The first column only includes S, firm and individual controls, but not G. Workers with exposure to imports of their specific machine earn 10.5 percent more than workers with no access to imports,

[9] An alternative way of controlling for unobserved firm heterogeneity would be to include firm fixed effects. We have tried this and obtained similarly sized, but much less precise estimates for α. The intuition for why firm fixed effect estimates are less precise is that they need both related and unrelated occupations *within the same firm*. Given that the sample only covers 6 percent of workers, such firms are very rare. In contrast, our estimate of β relies on all firms with unrelated occupations, including those who do not have a related occupation in the sample. Given a precisely estimated β, our α estimate is also precise.

conditional on firm and individual controls. It is also clear that, consistently with the previous literature, foreign ownership and firm size are positively related to wages.

The second column reports our preferred specification, including both S and G. Workers in unrelated occupations at importing firms earn 5.5 percent more than workers at non-importers. Relative to unrelated workers, those in related occupations earn 8.2 percent higher wage. The total wage premium of related occupations is hence 13.7 percent, but 8.2 percent is our preferred estimate for the causal effect.

Column 3 splits machine imports into two by the country of origin. "High-R&D countries" are the top 10 countries by the ratio of R&D expenditure to sales in the machinery sector. Machine imports from these countries are associated with a $5.3 + 7.2 = 12.5$ percent wage premium. This is significantly higher than the wage premium associated with imports from low R&D countries, 5.3 percent.

Column 4 replicates the same split for related and unrelated occupations. Workers in unrelated occupations at a firm which imports from a low-R&D country do not enjoy any premium over non-importing workers (in fact, the point estimate is negative). This suggests that there is no strong selection within this group of firms. By contrast, workers at a firm which imported from a high-R&D country earn $9.4 - 0.6 = 8.8$ percent more than non-importing workers, even if they work in occupations unrelated to the machine. It seems that firms importing from high-R&D countries are indeed "special." We are interested in, though, the wage effects over and above this firm selection effect. These are positive and significant, 4 percent for low-R&D countries and $4.0 + 4.1 = 8.1$ percent for high-R&D countries.

If firms that import machines hire better machine operators, then u_{it} will be correlated with S_{fot} and G_{ft}. We proxy for unobserved worker skill by exploiting the time dimension of the pseudo-panel discussed in Section 1.2. We add cell fixed effects to equation (3),

$$w_{ifot} = \alpha S_{fot} + \beta G_{ft} + \gamma X_{ft} + \delta Z_{it} + \xi_{ifo} + \nu_t + u_{ifot}, \tag{4}$$

where Z_{it} is now limited to the worker's age (other worker characteristics do not vary over time), ξ_{ifo} is a cell fixed effect and ν_t is a time fixed effect.

Table 5 shows the results of estimating equation (4). Now β can be interpreted as a differences-in-differences estimate: by how much the wage of workers changes after their employer imports its first machine relative to workers at non-importers? We see from columns 2 and 4 that there are no significant wage increases for

Table 5: Imported machines and wages: fixed effects

	(1)	(2)	(3)	(4)
	Log monthly earnings			
Imported machine specific to occupation	0.028***	0.032***	0.004	0.009
	(0.010)	(0.010)	(0.013)	(0.013)
Imported some machine		-0.019		-0.027*
		(0.014)		(0.016)
From high-R&D country:				
Imported machine specific to occupation			0.036***	0.032**
			(0.013)	(0.013)
Imported some machine				0.016
				(0.014)
Firm employment (log)	0.010***	0.010***	0.009***	0.010***
	(0.003)	(0.003)	(0.003)	(0.003)
Firm has majority foreign owner	0.029***	0.029***	0.028**	0.028**
	(0.011)	(0.011)	(0.011)	(0.011)
Individual controls	YES	YES	YES	YES
Cell fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
Observations	32,549	32,549	32,549	32,549
R-squared	0.862	0.862	0.862	0.862

Notes: All regressions control for age, age squared, cell and year fixed effects (coefficients not reported). Cells are defined by birth year, gender, educational attainment, firm and occupation. Sample is restricted to single-worker cells. Standard errors (in parantheses) are clustered by firm*year. *** p<0.01, ** p<0.05, * p<0.1 See text for sample definition and other details.

unrelated occupations.[10] By contrast, importing a machine related to the worker's occupation increases her wage significantly. The overall wage increase is about 3 percent (columns 1 and 2), and practically all of the effect comes from high-R&D imports (columns 3 and 4).

The fact that the wages of workers in affected occupations *increase* after imports suggest that machine imports do change the productivity and/or the wage setting at the firm. That this effect is confined to related occupations suggests that there is a technological reason for the link between imports and wages. Finally, the fact that only imports from high-R&D countries matter lends credibility to the idea that the wage gains are coming from the higher quality of these machines.

[10]This suggests that the positive estimated β in equation (3) might indeed be due to firm selection.

We now turn to asking how the returns to skill change with imported machines. Table 6 regresses log monthly earnings on an indicator of education (a dummy for completed high school), an import exposure indicator and their interaction. We are interested in whether the wage gap between primary and high-school graduates is larger among import-exposed workers. Column 1 shows that for workers with no access to imported machine (either because their firm did not import a machine, or it imported an unrelated machine), the high-school wage premium is 6.9 percent. For those exposed to imports of their related machine, the high-school premium is $6.9 + 4.4 = 11.3$ percent, a significant increase. In column 2, we ask whether this increase in the high-school premium is specific to importing *firms* or import-related *occupations*. We see that the the premium is higher by 1.5 percentage points at importing firms, even for occupations unrelated to the imported machine. This change in the premium is much smaller than that for related occupations ($1.5 + 3.4 = 4.9$ percent), and only marginally significant. Returns to experience (as proxied by worker age) are also higher on imported machines (not reported here).

In summary, imported machines seem to raise the return to observable skills, consistent with a model where machine quality and worker skill are complementary. It is such a model we turn to next.

3 A Model of Worker-Machine Assignment

In this section we develop a model of a small open economy, in which a constant supply of workers is matched with domestic and imported machines. Workers differ in skill, which is more productive on foreign machines than on domestic ones. Firms decide which machine to buy and what type of worker to hire as its operators.

Machines are indivisible. This nonconvexity leads to assignment and selection patterns that are very similar to models based on fixed cost of technology choice (Yeaple (2005)). There are no increasing returns to scale, however, and we can analyze a competitive equilibrium.

3.1 Workers

There is a mass L of workers, each possessing one from a continuum of skills. The range of potential skills is normalized to $[0, 1]$. Skills are distributed across workers according to a continuous distribution with density function $l(h) : [0, 1] \to$

Table 6: Imported machines and the returns to education

	(1)	(2)
	Log monthly earning	
Completed high school	0.069***	0.063***
	(0.004)	(0.006)
Imported machine specific to occupation	0.079***	0.061***
	(0.007)	(0.008)
Completed high school	0.044***	0.034***
* Imported machine specific to occupation	(0.007)	(0.008)
Imported some machine		0.046***
		(0.009)
Completed high school		0.015*
* Imported some machine		(0.009)
Firm employment (log)	0.070***	0.066***
	(0.003)	(0.003)
Firm has majority foreign owner	0.233***	0.227***
	(0.007)	(0.007)
Individual controls	YES	YES
Occupation*year fixed effects	YES	YES
Observations	98,225	98,225
R-squared	0.414	0.415

Notes: All regressions control for gender, age, age squared, and occupation*year fixed effects (coefficients not reported). Standard errors (in parantheses) are clustered by firm*year. *** p<0.01, ** p<0.05, * p<0.1 See text for sample definition and other details.

$\mathbb{R}$. Workers supply their labor inelastically and spend all their wage income on consuming the final good.

Suppose that there exists a continuous and strictly increasing wage function $w(h) : [0,1] \to \mathbb{R}$ giving the wage of a particular worker type h. We will later solve for this function in equilibrium.

3.2 Machines

There are two types of machines, domestic and foreign. Domestic machines have quality θ_D, and foreign machines have quality $\theta_F > \theta_D$.

Domestic machines are produced by competitive firms using a linear technology. It takes A units of the final good to produce a domestic machine. This pins down the price of the domestic machine in terms of the final good as $p_D = A$.

Foreign machines are imported from abroad in exchange for exports of the final good. The world price of foreign machines is exogenously given, and is not affected by local demand.

We assume that $p_F > p_D = A$, that is, foreign machines are traded at a premium. This premium comes from two sources. First, these machines are of a higher quality and arguably more expensive to produce. Second, the costs of transportation and tariffs raise the price of foreign machines, while leaving that of domestic machines unaffected. Trade liberalization can hence reduce the price of foreign machines.

In contrast to wages, machine prices are fixed exogenously. This follows from assuming a small open economy.

3.3 Firms

Each firm hires one worker and buys one machine to produce a final good.[11] Each firm produces the same product, the price of which we normalize to one.

Output increases in both the quality of the machine and the skill of its operator,

$$Q_i = F(\theta_i, h_i), \tag{5}$$

where Q_i is output of firm i, θ_i is the quality of its machine, and h_i is the skill of its operator. We assume that F is twice continuously differentiable and satisfies the Inada conditions. We also assume that $F_{\theta h} > 0$, that is, the production function is supermodular in machine quality and worker skill.[12]

Firms are identical ex ante. They hire workers and machines in competitive markets so as to maximize their profits. That is, they take the price of machines and the wages of workers as given. There is free entry into final good production.

The profit maximum problem can be written as

$$\max_{\{\theta_D, \theta_F\}, h} F(\theta, h) - p(\theta) - w(h). \tag{6}$$

Profits are revenues minus the price of a machine minus wages.

To ease exposition, the maximization problem can be broken into two steps: the firm first decides which machine to buy, then hires the right worker for it.

$$\max \left\{ \max_h F(\theta_D, h) - p_D - w(h), \max_h F(\theta_F, h) - p_F - w(h) \right\}$$

[11] We abstract from multiunit firms, because data do not permit us to investigate the within-firm assignment of machines to workers.

[12] It is straightforward to generalize our results for the case when machines produce differentiated products. This requires a stronger assumption of log supermodularity on F (see Yeaple (2005), Costinot and Vogel (2010)).

The first-order condition for optimal worker hiring is

$$F_h(\theta_D, h_D) = w'(h_D) \tag{7}$$

if the firm has chosen the domestic machine, and

$$F_h(\theta_F, h_F) = w'(h_F) \tag{8}$$

if it has chosen the foreign one.

Let $\pi_D = \max_h F(\theta_D, h) - p_D - w(h)$ denote the maximum profit attainable with a domestic machine, and $\pi_F = \max_h F(\theta_F, h) - p_F - w(h)$ the maximum profit on a foreign machine. Clearly, the firm decides to buy an imported machine if and only if $\pi_F \geq \pi_D$, and is indifferent if $\pi_F = \pi_D$.

3.4 Equilibrium

Because firms are identical ex ante, it is indeterminate which firm hires which worker. However, the assignment of machines to workers will be pinned down in equilibrium.

Definition 1. *An equilibrium in this economy is (i) a matching function* $\Theta : [0,1] \to \{\theta_D, \theta_F\}$ *that maps worker skill to machine quality, (ii) a wage function* $w : [0,1] \to \mathbb{R}$*, (iii) a final good output function* $q : [0,1] \to \mathbb{R}$ *that gives the amount of final good produced by firms employing type-h workers, (iv) the price* p_D *and amount* M_D *of domestic machine production, (v) and the amount* M_F *of machine imports such that*

1. *each worker is employed,*
2. h *solves solves* (6) *for a machine of type* $\Theta(h)$*,*
3. *final good and domestic machine producers make zero profit,*
4. *and trade is balanced.*

Proposition 1. *The equilibrium is characterized by a strict sorting of workers of various skills onto the two types of machines. There exists a cutoff* $h^* \in [0,1]$ *such that all workers below this cutoff work on domestic machines, and all workers above this cutoff work on foreign machines. The matching function is a step function,*

$$\Theta(h) = \begin{cases} \theta_D & \text{if } h \leq h^*, \\ \theta_F & \text{if } h > h^*. \end{cases}$$

The wage function is

$$w(h) = \begin{cases} F(\theta_D, h) - p_D & \textit{if } h \leq h^* \\ F(\theta_F, h) - p_F & \textit{if } h > h^*. \end{cases},$$

We prove this proposition by constructing the equilibrium step by step.

Labor market clearing and profit maximization. Consider labor markets first. There is a positive supply of workers at each skill level h, which means that there has to be a positive labor demand and positive production $q(h)$ at each skill level.

For a firm to produce at skill level h, it has to break even. The profit of a type-h firm is

$$\max\{F(\theta_D, h) - p_D, F(\theta_F, h) - p_F\} - w(h).$$

The wage of a type-h worker is hence

$$w(h) = \max\{F(\theta_D, h) - p_D, F(\theta_F, h) - p_F\}.$$

Because $F(\theta_F, h) - F(\theta_D, h)$ is strictly increasing in h, there is a complete separation of operators of foreign and domestic machines. All workers below a cutoff skill h^* work on domestic machines, and all workers above this cutoff work on foreign machines.

The cutoff h^* is implicitly defined by

$$F(\theta_F, h^*) - F(\theta_D, h^*) = p_F - p_D. \tag{9}$$

This condition is intuitive. At the skill level h^*, the firm is indifferent between buying a domestic or a foreign machine. The productivity advantage of a better foreign machine is exactly offset by its higher price. Clearly, h^* increases in the price difference $p_F - p_D$.

It is easy to verify that the derivative of the wage function,

$$w'(h) = \begin{cases} F_h(\theta_D, h) & \text{if } h \leq h^* \\ F_h(\theta_H, h) & \text{if } h > h^* \end{cases}$$

satisfies the first-order conditions for profit maximum.

Figure 1 illustrates the sorting of workers onto domestic and foreign machines and the resulting wage function. The wage function is the upper envelope of the curves $F(\theta_D, h) - p_D$ and $F(\theta_F, h) - p_F$. By assumption of machine-worker complementarity, the latter curve is steeper than the former. The curves intersect at h^*.

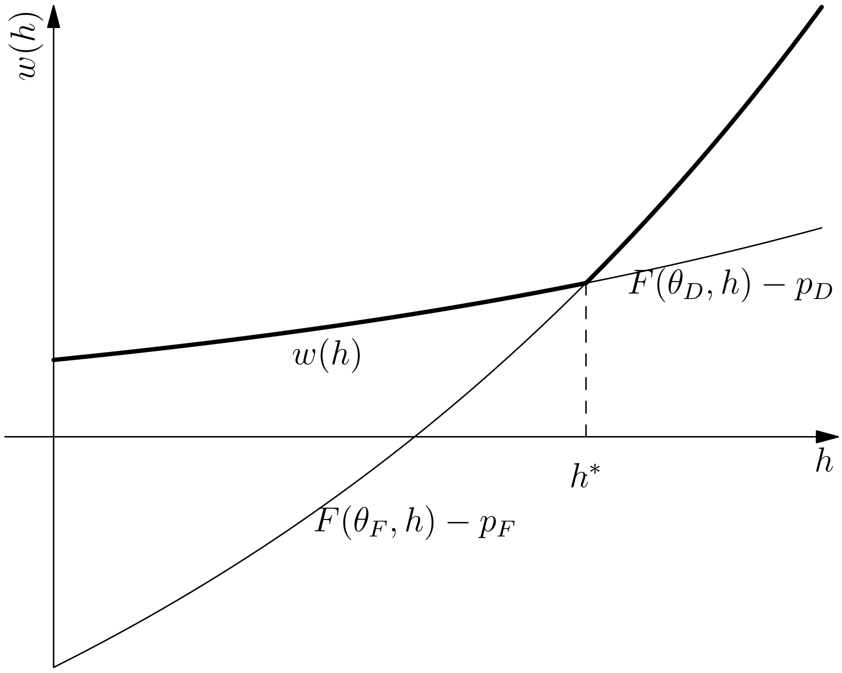

Figure 1: The wage function

Goods market clearing. The supply of type-h firms is $q(h) = F(\Theta(h), h)l(h)$. The total supply of the final good is hence

$$Q = \int_0^{h^*} F(\theta_D, h)l(h)dh + \int_{h^*}^1 F(\theta_F, h)l(h)dh.$$

All $l(h)$ workers are employed on a suitable machine, and we integrate over all the skill levels to obtain aggregate output.[13]

The total demand for domestic machines is

$$M_D = \int_0^{h^*} l(h)dh = L(h^*),$$

where $L()$ is the cumulative distribution function of $l()$. The intuition is that every worker below skill level h^* will be assigned a domestic machine.

Each domestic machine requires A units of the final good, so

$$Q_D = AM_D = AL(h^*)$$

units of the final good are sold for domestic machine producers.

Trade balance implies that machine imports equal final good exports in value,

$$Q_F = p_F M_F,$$

[13]This is different from Melitz (2003) and Yeaple (2005), who assume that firms produce differentiated goods and engage in monopolistic competition.

where

$$M_F = \int_{h^*}^{1} l(h)dh = L - L(h^*)$$

is the number of foreign machines needed to employ the remaining workers.

The remaining part of production,

$$Q_C = Q - Q_D - Q_F$$

is consumed, and it follows from Walras' law, that this is exactly the amount demanded for consumption. Given that there are no profits in the economy, consumption equals the total wage bill, wL.

This completes the characterization of the equilibrium.

From Figure 1 it is clear that workers using an imported machine are (i) more skilled, (ii) earn higher wages than those on a domestic machine. They also have a higher return to skill than if they worked on a domestic machine. All these predictions are consistent with the evidence discussed in Section 2.

3.5 Trade liberalization

Consider a reduction in the tariffs levied on imported machines. What is the effect of this liberalization in this economy? Which firms will upgrade to better foreign machines? What is the effect on wages?

We study unilateral liberalization that only affects imports, not exports. We want to focus on import liberalization, the effects of which are less understood than those of export liberalization. Also note that in our model all firms are indifferent between exporting or not because there are no fixed costs of exporting. That is, even if we allowed for multilateral liberalization, all firms would be affected symmetrically by the increasing export demand.

As tariffs decline, so does the price of of foreign machines: $\tilde{p}_F < p_F$. (This is a small open economy.) The lower $\tilde{p}_F$ raises the profitability of firms using foreign machines. In equilibrium, a wider range of firms will use imported machines.

Figure 2 illustrates the comparative static exercise. As p_F declines to $\tilde{p}_F$, the wage curve of importers shifts upward, and the skill cutoff h^* decreases to $\tilde{h}$. As imported machines become cheaper, they become available for a wider range of workers.

Workers (and firms) can be split into three groups. Workers with skill level between 0 and $\tilde{h}$ continue to use domestic machines. Workers between $\tilde{h}$ and h^* used

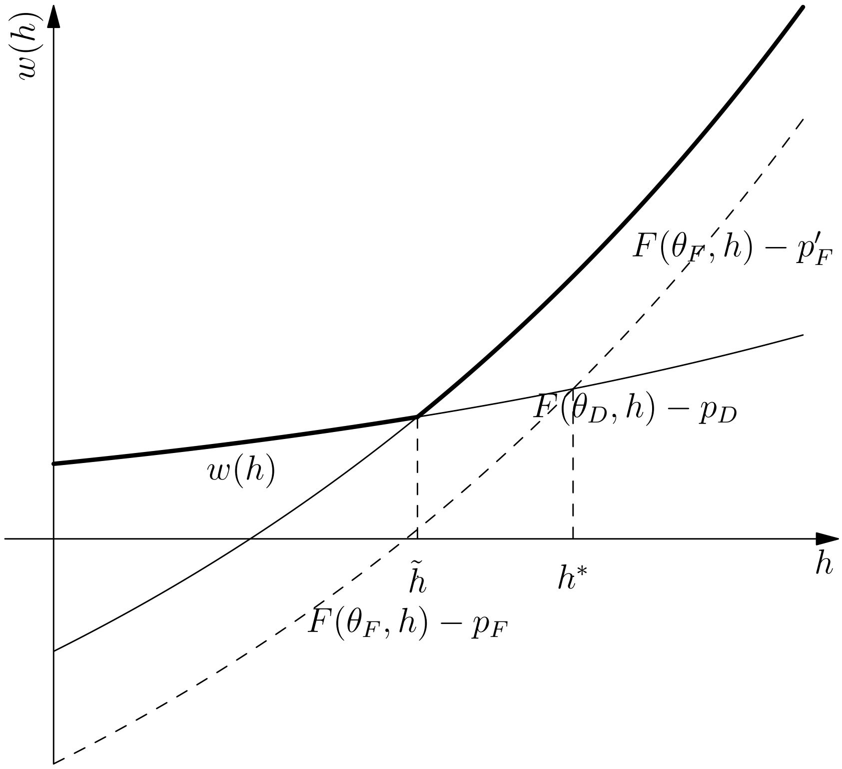

Figure 2: Trade liberalization and worker-machine assignment

domestic machines before, but switch to an imported machine after liberalization. Workers above skill level h^* continue to use imported machines.[14]

The new function is denoted by $\tilde{w}(h)$. Switchers enjoy a wage gain of $F(\theta_F, h) - F(\theta_D, h) + p_D - \tilde{p}_F$, even while h is held fixed. This is consistent with evidence that workers whose employer has purchased a foreign machine receive higher wages afterwards, controlling for (synthetic) individual fixed effects.

Interestingly, continuing importers also enjoy wage increases. This is due to a general equilibrium effect. Because imported machines are now cheaper, if skilled wages remained the same, new entrants would make a profit by buying an imported machine and hiring a skilled worker. Competition for the most skilled workers increases their wage, even if in equilibrium their employer does not upgrade their machine.

In addition to matching the empirical findings discussed in Section 2, the model yields two interesting testable predictions. The first considers the *timing* of im-

[14]Strictly speaking, we cannot make similar statements about firms, because a firm with an h_1 worker before liberalization can freely fire her and hire an h_2 worker instead. This is because all potential input combinations bring zero profit for all firms. We can, however, introduce the tie-breaking rule that a firm does not fire its workers unless this brings positive profits. This can be motivated by infinitesimal hiring or firing costs. In this case, all firms retain their workers, and we can refer to firms and workers interchangeably.

ports. Firms with the best workers start importing first. The productivity of their skilled operators makes it profitable for them to buy the better machine even when tariffs are high. As tariffs continue to fall, the threshold of importers keeps falling and firms with worse and worse workers start importing.

We take this prediction to the data. Because worker skills are unobservable, we use the ranking of the worker within the wage distribution of her occupation as a proxy. In the model, there is a monotonic relationship between skill and wage rank: the most skilled workers will receive the highest wages, and so on.[15] Conveniently, the rank has the same $[0, 1]$ support as the skill distribution.

Looking at workers in the sample in 2003, we ask when their firm first started importing their specific machine. Workers are split into two groups: "early importers" are those who were among the first 50 percent of workers to receive imported machines. That is, at the time of their machine import, less than 50 percent of workers in their occupation had already been exposed to imported machines. "Late importers" are the complementary group, those who purchased their imported machine when already more than 50 percent of workers had one.[16]

Figure 3 plots the kernel density estimates of the wage rank of workers within the two groups. The unconditional density of wage rank is the uniform density on $[0, 1]$. Relative to the unconditional density, the better workers (above the median) are overrepresented among early importers, and underrepresented among late importers. This pattern is clearly consistent with the model, as lower ranked workers are seen to switch to imported machines later.

The second prediction is that as imported machines become more widespread, even those who are already on an imported machine gain higher wages. To check this prediction in the data, we ask how the prevalence of importing within a worker's occupation affects her wages. More specifically, for each worker in each year we calculate the fraction of workers in the same occupation who already have an imported machine. In the model, this fraction corresponds to $1 - L(h^*)/L$. Because importer wages decrease in h^*, they should increase in the prevalence of importers.

We regress the (log) wage of a worker on her import dummy and its interaction with the fraction of workers already importing. Table 7 reports the results.

[15]It is important to use the rank, rather than the actual wage to proxy for skill. Actual wage is affected by not only the machine the worker is operating, but also by the entire equilibrium assignment. The wage rank, however, only depends on h because $w(h)$ is always strictly increasing.

[16]Strictly speaking, we cannot be sure that these operators worked at the same firm when the imports took place. When we repeat the exercise using the worker sample at the time of imports, we get very similar results.

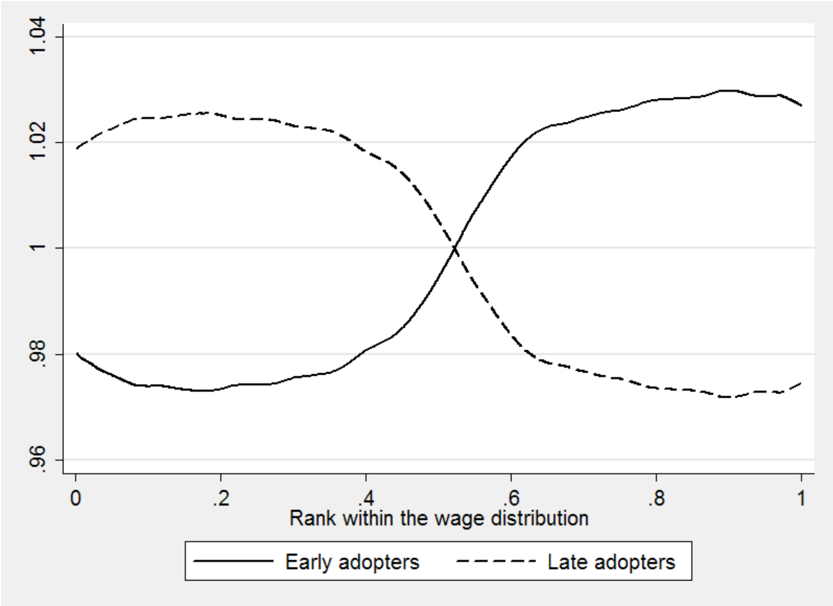

Figure 3: Distribution of workers by the time of their first import

Regressions include firm size and foreign ownership and occupation×year fixed effects, and individual controls. Because occupation trends soak up the variation in import prevalence, we can only evaluate its interaction with the import dummy. As predicted by the model, the prevalence of imports affects importers more than non-importers.

The mean within-occupation prevalence of importers is 0.46. In an occupation×year with this prevalence, the wage gap between importers and non-importers is $0.46 \cdot 11.8 + 4.7 = 10.1$ percent. When import prevalence rises to its 75th percentile, 0.69, the wage gap increases to 12.8 percent.

4 Robustness

In this section, we offer some robustness checks of the main results on the wage gap between importers and non-importers. We study robustness to measurement error in our import exposure dummy or in the occupation classification, working with different samples, and separating the effect of foreign and domestic ownership.

We estimate our main specification, equation (3) in various alternative specifications. Table 8 reports the results. For convenience, column 1 reproduces the baseline specification, reported in column 2 of Table 4.

Column 2 reports the results of the regression when run on only those occupations that have a single worker at the firm. (In the baseline specifications we allowed for up to 20 workers in the same occupation.) This minimizes the measure-

Table 7: Import prevalence and wages

	(1)	(2)
	Log monthly earnings	
Imported machine specific to occupation	0.047***	0.054***
	(0.013)	(0.014)
* import prevalence	0.118***	0.054**
	(0.023)	(0.026)
Imported some machine		-0.036**
		(0.017)
* import prevalence		0.144***
		(0.026)
Firm employment (log)	0.071***	0.065***
	(0.003)	(0.003)
Firm has majority foreign owner	0.232***	0.224***
	(0.007)	(0.007)
Individual controls	YES	YES
Occupation*year fixed effects	YES	YES
Observations	98,225	98,225
R-squared	0.414	0.416

Notes: All regressions control for gender, a dummy for completed high school, age, age squared, and occupation*year fixed effects (coefficients not reported). Standard errors (in parantheses) are clustered by firm*year. *** p<0.01, ** p<0.05, * p<0.1 See text for sample definition and other details.

ment error stemming from the fact that we do not know *who* within the affected occupation actually receives the machine. Consistent with smaller attenuation bias, the estimated effect of import exposure is indeed larger, 9 percent, though this is not statistically different from the baseline estimate of 8 percent. Also note that this specification severely restricts the sample, and the sample size drops to one fifth.

Column 3 reproduces the same regression as column 1, run on the sample that is used in the pseudo-panel specification (Table 5). In this sample, we only use workers that are uniquely identified by their gender, year of birth, schooling and occupation, and are staying at the firm for at least four years. Again, the sample is much smaller than in the baseline specification, but the wage effect of imported machines is similar.

Because our identification relies heavily on the occupation descriptions, one might worry about reporting error in the occupation code. We address this issue

Table 8: Robustness to alternative specifications

	Log monthly earnings						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Baseline	Singleton cells only	Panel sample	Mismeasured occupation codes	Firms above 50 employees	Domestic firms	Foreign firms
Imported machine specific to occupation	0.082***	0.091***	0.088***	0.059***	0.072***	0.084***	0.089***
	(0.007)	(0.008)	(0.009)	(0.005)	(0.007)	(0.008)	(0.012)
Imported some machine	0.056***	0.042***	0.080***	0.064***	0.050***	0.031***	0.146***
	(0.007)	(0.007)	(0.010)	(0.005)	(0.008)	(0.008)	(0.023)
Firm employment (log)	0.066***	0.066***	0.039***	0.082***	0.064***	0.076***	0.037***
	(0.003)	(0.003)	(0.004)	(0.002)	(0.003)	(0.004)	(0.005)
Firm has majority foreign owner	0.227***	0.249***	0.232***	0.248***	0.219***	-	-
	(0.007)	(0.008)	(0.009)	(0.005)	(0.007)	-	-
Individual controls	YES	YES	YES	YES	YES	YES	YES
Occupation*year fixed effects	YES	YES	YES	YES	YES	YES	YES
Observations	98,225	21,396	32,549	264,606	84,770	70,074	28,151
R-squared	0.415	0.322	0.447	0.379	0.408	0.374	0.411

Notes: All regressions control for gender, a dummy for completed high school, age, age squared, and occupation*year fixed effects (coefficients not reported). Standard errors (in parantheses) are clustered by firm*year. *** p<0.01, ** p<0.05, * p<0.1 See text for sample definition and other details.

the following way. The Hungarian Statistical Office reports a list of "related but distinct occupations" for each occupation. For example, "spinners," "weavers," and "knitters" are related to, but distinct from "textile machine operators." To allow for the possibility of miscoding, we group all related occupations together and rerun the main specification on this dataset. The results are reported in column 4. Because we also look at related occupations, there are many more workers in the sample (264,606). The effect of imported machines on wages is similar, though somewhat smaller. This is consistent with the notion that the original coding does contain some useful information about the worker's occupation, which we lose when grouping different occupations together.

Column 5 reports regression results for large firms only. The wage premium of importers is similar, though somewhat smaller, potentially because the chances of false positives (assigning the imported machine to someone not exposed to it) is larger in large firms.

Columns 6 and 7 split the sample into domestically and foreign-owned firms. The baseline estimates are very similar, suggesting that there are no large differences in the skill-complementarity of imports between domestic and foreign firms. At the same time, importers tend to pay much higher wages to unaffected workers among foreign firms than among domestic firms. This suggests that there may be complementarities between the different modes of global engagement (imports, foreign investment) of the firm. We wish to study such complementarities in future research.

5 Conclusion

This paper estimated the effect of capital imports on the wages of a large, representative sample of Hungarian machine operators. Using linked employer-employee data and detailed product- and firm-level import data, we matched the precise occupation description of each worker to the equipment imported by their employers. We found that machine operators working on imported machines earn 8 percent more than those working on domestic machines. Estimating a structural assignment model of heterogenous workers and machines, we concluded that about one third of this wage gap is due to the higher returns to skill on imported machines, and two thirds are due to the higher skill of imported machine operators. Our structural estimates also suggest that imported machines contributed substantially to the increase in wage inequality in Hungary. Our results highlight a novel mechanism of skill-biased technical change.

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A Data Appendix

A.1 Matching machines to their operators

We match the 4-digit FEOR occupation code of machine operators to the 6-digit Harmonized System product code of capital goods. There are 61 FEOR codes involving the operation of a machine (excluding vehicle drivers), see Table A.1.

There are 260 HS codes describing specialized machines and instruments. We match each occupation to at least one, potentially several machines that they can be working on. The matching is done as follows.

Table A.1: List of machine operating occupations in the data

FEOR	Description
8111	Food products machine operators
8112	Beverage products machine operators
8113	Tobacco products machine operators
8121	Textile industry machine operators and production-line workers
8122	Dressmaking machine operators and production-line workers
8123	Leather tanning and processing machine operators and production-line workers
8124	Shoemaking machine operators and production-line workers
8125	Wood processing machine operators and production-line workers
8126	Paper and pulp industry machine operators
8127	Printing machine operators
8129	Light industry machine operators and production-line workers n.e.c.
8131	Petroleum refinery and processing machine operators
8132	Gas-making and processing machine operators
8133	Basic chemicals and chemical products machine operators
8134	Pharmaceutical products machine operators
8135	Fertilizer and plant-protection products machine operators
8136	Plastic processing machine operators
8137	Rubber goods manufacturers, vulcanizers
8141	Ceramic products machine operators
8142	Fine ceramics products machine operators
8143	Glass and glass-products machine operators
8144	Concrete building block machine operators
8145	Lime and cement products machine operators
8149	Building materials industry machine operators n.e.c.
8191	Metallurgical machine operators
8192	Metal working machine operators
8193	Production-line assemblers
8199	Processing machine operators, production-line workers n.e.c.
8211	Solid minerals extraction machine operators
8219	Mining-plant operators n.e.c.
8221	Power-production and transformation plant mechanics and operators
8222	Coal- or oil-fired power-generating plant operators
8223	Nuclear-fuelled power-generating plant operators
8224	Hydroelectric power-generating station mechanics and machine operators
8229	Power production and related plant operators n.e.c.
8231	Water works machine operators
8232	Sewage plant operators
8233	Water pump operators
8239	Water treatment plant operators n.e.c.
8240	Packaging-machine operators
8291	Boiler operators (licensed boilermen)
8292	Decontaminating machine and equipment operators
8293	Agricultural machine operators, mechanics
8299	Other non-manufacturing machine operators n.e.c.
8311	Agricultural engine drivers and operators
8312	Forestry plant operators
8313	Plant protection machine operators
8319	Agricultural and forestry mobile-plant drivers, operators n.e.c.
8321	Earth moving equipment operators
8322	Groundwork machine operators
8323	Road, bridge and railroad building machine operators
8324	Hydromechanical and floating plant operators
8325	Well drilling machine operators
8329	Construction machine operators n.e.c.
8331	Scavengery machine operators and drivers
8332	Cesspool-pumping, sewage-collecting truck operators
8341	Crane operators
8342	Elevator and conveying machine operators
8343	Lift-trolley operators
8344	Loading/unloading machine operators
8349	Material conveying machine operators n.e.c.

Table A.2: Tags used for machines and occupations

agriculture, assembly, basic metals, beverage, cement and concrete, ceramics, chemicals, cleaning, construction, electric, fabricated metals, food, glass, heating and cooling, leather, mining, moving, oil and gas, other, packaging, paper, pharmaceuticals, plastic, power, printing, radiation, rubber, stone and minerals, textile, tobacco, vehicle, vessel, water, wood

First, we tagged both occupations and products with simple tags relating to the broad industry in which they might operate. We used 34 tags (Table A.2). Each occupation or product could have received multiple tags. Among the occupation–machine matches that have at least one tag in common, we used the detailed description of the occupation to narrow down the set of machines that are used by this worker. This procedure was carried out independently by five people, and we selected the matches that were flagged by at least three of them. (Results are robust to different cutoffs.) This resulted in 354 matches.

The average worker is matched with 5.5 machines, and the average machine is matched with 1.3 occupations. Table A.3 displays 20 randomly selected matches. The full list of matches is available upon request.

Table A.3: A list of 20 randomly selected matches

FEOR	Occupation description	HS6	Product description
8112	Beverage products machine operators	843880	Industrial machinery nes for food, drink preparation
8121	Textile industry machine operators and production-line workers	844519	Textile fibre preparing machines nes
8125	Wood processing machine operators and production-line workers	846595	Drilling or morticing machines for wood, etc
8125	Wood processing machine operators and production-line workers	846596	Splitting, slicing or paring machines for wood, etc
8192	Metal working machine operators	846040	Honing or lapping machines
8192	Metal working machine operators	846190	Metal cuttting, shaping, filing, engrave machines, nes
8192	Metal working machine operators	846221	Num controlled machine tools to bend, fold, etc, metal
8199	Processing machine operators, production-line workers n.e.c.	847940	Rope or cable-making machines
8222	Coal- or oil-fired power-generating plant operators	840681	Turbines n.e.s., of output <40mw
8222	Coal- or oil-fired power-generating plant operators	850239	Electric generating sets
8224	Hydroelectric power-generating station mechanics and machine operators	841011	Hydraulic turbines, water wheels, power < 1000 kW
8293	Agricultural machine operators, mechanics	842481	Agricultural sprays and powder dispersers
8293	Agricultural machine operators, mechanics	843210	Ploughs
8299	Other non-manufacturing machine operators n.e.c.	842489	Sprays/powder dispersing machines except agricultural
8311	Agricultural engine drivers and operators	843210	Ploughs
8319	Agricultural and forestry mobile-plant drivers, operators n.e.c.	843352	Threshing machinery nes
8323	Road, bridge and railroad building machine operators	843049	Boring or sinking machinery nes, not self-propelled
8323	Road, bridge and railroad building machine operators	843050	Construction equipment, self-propelled nes
8325	Well drilling machine operators	843049	Boring or sinking machinery nes, not self-propelled
8344	Loading/unloading machine operators	842790	Trucks with lifting/handling equipment, non-powered