Machines and Machinists: Importing Skill-Biased Technology*

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Abstract

Which workers gain and which workers lose from technical change? We study the wage effects of new, imported machinery in Hungary between 1988 and 2004 through the lens of a model. In our model, new machines are faster and more reliable than old ones. Both characteristics complement worker skill: better workers will be assigned to new machines, where their productivity and wage will increase. We confirm these model predictions in a case study and in a representative sample of Hungarian manufacturing machine operators. Workers assigned to imported machines earn about 5 percent more than similar workers at similar firms. The returns to formal education and unobserved skills are higher on imported machines. The increased availability of imported machinery due to trade liberalization is responsible for about 40 percent of the increase in wage inequality in our sample. Our results suggest that imported machines can help propagate skill-biased technical change.

Which workers gain and which workers lose from technical change? To identify the groups at risk, we need to study the precise patterns of complementarity between technology and workers. A large literature discusses such complementarities with general purpose technologies such as mass production, automation and computerization.[1] These are relevant for rich countries on the technology frontier, but less so for poorer countries for which low-technology equipment still account for the vast majority of investment.

Improved quality of industrial machinery, such as increased speed and reliability, has historically served as a major source of productivity growth, especially at earlier stages of development. Producing a yard of cloth in the U.S. required 40 minutes of loom time and operator time in 1819, but only 13 minutes of loom time and 1 minute of operator time in 1903.[2] Incremental technology improvements were pervasive more recently and in other sectors, too. The quality of durable equipment produced in the U.S. has almost tripled between 1947 and 1983.[3] And these

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[1] We discuss the relevant literature below.

[2] Bessen (2012, Table 3)

[3] Gordon (1990, Chapter 3)

improvements are especially important in poorer countries, where economic growth is mostly driven by investment in traditional equipment.[4]

To understand the labor market effects of simple industrial machinery, we build a model of how machine quality and operator skill interact and use it to study within-firm machine assignment and operator wages. New machines differ in two aspects from old ones: they are faster and they require less operator attention. The former improvement is skill augmenting, the latter is skill replacing. From the machine-level production function, then, it is not a priori clear whether new machines are skill augmenting or skill replacing.

Our first result is that when firms optimally allocate machines to workers, the skill replacement effect disappears. In the worker-level production function, new machines are unambiguously skill augmenting: they will be assigned to better workers. Because in our model new machines have higher productivity, workers using such machines earn higher wages.[5] And because they are skill augmenting, the wage premium associated with new machines is increasing in worker skill.

We evaluate the model in data on Hungarian manufacturing firms. Hungary provides an ideal laboratory for this analysis. The sudden fall of communism resulted in rapid trade liberalization, especially towards technologically advanced countries of the European Economic Community. As we document below, machines imported from these countries were better than older Hungarian or Soviet machines.[6] First, we illustrate the mechanism of the model in a case study of a Hungarian weaving mill during 1988–1997. In this period, the weaving mill replaced most of its outdated looms with new imported ones. The new looms have more than twice as high potential output and face 5 percentage point lower operator-related downtime. Consistently with the model, better skilled workers are assigned to the new looms, where their productivity and wages increase. Moreover, the productivity returns to worker skill are higher on new machines, and the returns to new machines are higher with better workers.

To document the effects of machine improvement in other industries, we turn to a sample of Hungarian machine operators between 1992 and 2004. In this period, the exposure to new, imported machinery has increased from 17 percent of workers to 47 percent. The trajectory of trade liberalization was mostly driven by Hungary's European accession: the 1991 Interim Association Agreement stipulated a rapid phaseout of tariffs, with some heterogeneity across machines and other industrial goods. We exploit this liberalization as an exogenous shifter of the technology available to Hungarian firms.

We find that machine operators exposed to new machinery earn 5 percent more than similar workers at similar firms. We also find that firm-occupation groups with many high-skill workers are the first to start importing. While this selection on skill is consistent with the model

[4] As Jorgenson & Vu (2007) estimate, even in the 2000s, about 80 percent of capital contribution to growth is coming from non-ICT investment in developing and transition economies. By contrast, the average share for developed countries is about one half. Raveh & Reshef (2016) show that, in a panel of 21 less developed countries, the share of low-tech equipments imports ranges between 40 and 70 percent.

[5] This requires that firms share the rent stemming from greater productivity with workers (Card, Cardoso, Heining & Kline 2018).

[6] Sutton (2001) discusses survey evidence that Japanese and Taiwanese metal working machines imported to India are better in reliability, accuracy and productivity than domestic ones. And historically, Clark (1987) documents large heterogeneity in textile loom productivity across countries.

prediction that new machines are skill augmenting, it poses a challenge for identifying the causal effect of importing on wages. Using tariffs interacted with firm size as an instrument for actual importing and including firm-year fixed effects to capture any firm-level unobserved variation, reduces the effect of new machine on operator wage to 3 percent. And our estimates imply that the returns to both observable and unobservable skills increased sharply with importing.

Our findings suggest that access to new machinery can contribute to increased earnings inequality among workers.[7] Burstein, Cravino & Vogel (2013) and Parro (2013) make a similar point with multi-country general equilibrium models. Our paper studies the skill bias of new machinery in micro data and proposes a novel theoretical mechanism.

A large literature discusses complementarities of skilled and unskilled labor with general purpose technologies such as steam engines (Katz & Margo 2014, Franck & Galor 2015), electrification (Goldin & Katz 2008, Chapter 3), mass production and its dissolution (Piore & Sabel 1984) and automation (Autor 2015, Acemoglu & Restrepo 2017). The impact of information and communication technology (ICT) is particularly well researched. Several studies have documented that ICT investments depreciate routine skills (Levy & Murnane 1996, Autor, Levy & Murnane 2003), thereby raising the relative productivity of skilled workers (Akerman et al. 2013). ICT increases the attractiveness of complementary investments in work organization and product innovations, which further boost the relative demand for skilled labor (Bresnahan, Brynjolfsson & Hitt 2002). ICT also reshapes human resource management, leading to a better selection of workers and higher productivity (Ichniowski, Shaw & Prennushi 1997). In contrast to these papers, and closer to our focus, Lindner, Muraközy & Reizer (2018) study low-novelty innovation activities such as process innovation and conclude they are skill biased.

Most previous studies of globalization and wages have concentrated on linking firm-level wage differentials to trade exposure (Helpman, Itskhoki, Muendler & Redding 2012, Verhoogen 2008, Bustos 2011). This literature started out focusing on the effects of exporting, showing that exporters pay higher wages than non-exporters.[8] Importing is also associated with higher wages, and several studies found that importing machinery or intermediates raises the demand for skill.[9] By contrast, Amiti & Cameron (2012) found that reducing input tariffs reduces the skill premium within Indonesian plants. Using Chilean data, Pavcnik (2003) found that imported materials, foreign technical assistance, and the use of patented technology did not exert influence on skill shares and relative wages once she controlled for unobserved plant

[7]Note that earnings inequality increases even within narrow occupations: some (more skilled) workers will have access to new machines, some others in the same occupations will not. Much of this variation is across firms (larger firms are more likely to import), but some are within the firm. While some studies find that across-firm heterogeneity accounts for the rise in wage inequality in the U.S. (Barth, Bryson, Davis & Freeman 2016) and Germany (Card, Heining & Kline 2013), for example, Akerman, Helpman, Itskhoki, Muendler & Redding (2013) document that most of the recent increase in Sweden is due to within-firm wage inequality. Spitz-Oener (2006) documents that a large fraction of the increased demand to skill in Germany is due to within-occupation skill upgrading.

[8]See Bernard, Jensen & Lawrence (1995) for the U.S., Amiti & Davis (2012) for Indonesia, Brambilla, Lederman & Porto (2012) for Argentina, Schank, Schnabel & Wagner (2007) for Germany, Frias, Kaplan & Verhoogen (2012) for Mexico, and Krishna, Poole & Senses (2011) for Brazil.

[9]See Harrison & Hanson (1999) for Mexico, Kasahara, Liang & Rodrigue (2016) for Indonesia, Frazer (2013) for Rwanda, and Hummels, Jørgensen, Munch & Xiang (2014) for Denmark. This latter study is the closest to ours as it uses detailed product and occupation classifications to differentiate the wage effects of importing.

characteristics. Her study had no data on imported machinery.

In contrast to this literature, we focus on within-firm wage inequality, showing how imported technology can lead to increasing wage differences across job-cells and higher inequality within firms (and job cells).[10] We look at a homogeneous group of relatively low-skilled workers whose productivity is unlikely to increase for reasons other than changes in the machinery they work with.[11] Homogeneity also diminishes the risk that we mistakenly attribute the rising returns to skills, a multifaceted process, to technological change.[12]

Section 1 introduces our model. We build an engineering production function in the spirit of Arrow, Levhari & Sheshinski (1972) and Bessen (2012). New machines are both faster and more reliable. Faster machines require more skilled operators to avoid costly downtimes. And more reliable machines require less skilled operators, as the machine faces less downtime anyway.

We then characterize the optimal within-firm assignment of workers to machines using optimal transportation methods. Interestingly, when firms optimize assignment, the skill replacing effect of reliability disappears. This is because skilled workers can operate more new machines than old, unreliable ones. The firm will internalize this and assign skilled workers more new machines instead of a few old ones.[13]

Because firms engage in rent sharing (Card et al. 2018), these complementarity effects in machine productivity will show up in worker wages. We conclude this section with a list of testable predictions for the cross section of workers as well as a comparative static exercise for trade liberalization, which makes new machines cheaper.

Section 2 describes the case study of the weaving mill. The benefit of this case study is that the internal data of the firm records individual assignment of workers to different types of looms, and direct measures of worker and machine productivity. We provide statistical analysis of worker-machine assignment, worker wages and machine productivity.

Section 3 describes our larger dataset of manufacturing workers. The richness of the data permits us to focus on operators of specialized manufacturing machinery, who are most likely to be directly affected by machinery imports. Relative to the case study, this data covers a larger number of firms and workers in a wider range of sectors. The drawback is that we have fewer observables for each firm and worker. We do not see the assignment of individual workers to machines or individual machine productivity. But, as we describe in Section 3, we can infer access to new machines at the firm-occupation level.

Section 4 describes basic patterns in tariffs, importing, and wages. We use Hungarian linked employer-employee data from 1992-2004. Hungary, like many other countries other than top

[10]Supporting our findings, Frias et al. (2012) present evidence that exposure to international trade increased within-plant inequality in Mexico.

[11]Intensive on-the-job training could be an alternative, but less so in Hungary, where the participation of low-educated workers in formal and informal skill-enhancing activities is notoriously low (Köllő 2017).

[12]Recall the criticism of Krueger (1993) by DiNardo & Pischke (1997), who demonstrated that pencil and phone usage, as well as sitting rather than standing during work, were as good predictors of growing wage returns as was ICT usage.

[13]Our model predictions are consistent with historical patterns of textile worker productivity: Clark (1987) shows that in 1910, New England textile operatives operated six times as many looms as low-productivity operatives in China, Greece or India; and, in the United States, a weaver in 1903 was using 15 power looms relative to the one hand loom used in 1819 (Bessen 2012).

industrial economies (Eaton & Kortum 2001), imports a large fraction of its machinery. We describe the evolution of wage inequality among machine operators, the trends in occupation-level imports, and the timing of importing by firms. The main pattern is that both the return to skill and the within-occupation inequality have increased.

In Section 5 we estimate how new machines affect machine operator wages. The key identification challenge is that worker skill and firm productivity are unobserved, and correlated with both import behavior and worker wage. We address this problem in three ways. First, we include rich controls for worker and firm observables. Second, we include firm-time fixed effects to control for time varying firm unobservables such as firm productivity. Third, we instrument import choice with tariffs that are plausibly uncorrelated with both unobservables.

The estimated wage effects of new, imported machines are similar in our case study and in our broader sample. They are the same order of magnitude as the returns to having a high school education and the returns to computer use, as reported by Spitz-Oener (2008) and Dostie, Jayaraman & Trépanier (2010). We also see that, consistently with the model, the returns to skill are higher on new machines. And, as one would expect if some of the skills were unobservable, the wage effects of importing are greater in upper quantiles of the wage distribution.

1 A model of machine productivity, worker assignment and wages

We build a model with heterogeneous workers and machines. Workers are machine operators differing in skill: how quickly they can solve problems with their machine. Machines differ in two dimensions of quality: speed (output per unit of run time) and the level of attention required. Better machines produce more output and require less operator attention.[14]

First we lay out the production function and show that better machines can be either skill augmenting and skill replacing. Fast machines are skill augmenting, whereas reliable machines are skill replacing. We then study the optimal assignment of machines to workers within the firm and derive the wage equation. Finally, we discuss the effects of trade liberalization, which makes new machines cheaper.

1.1 The machine-level production function

Motivated by Arrow et al. (1972), we set up the following production function. A machine of type m produces A_m units of output per unit of time if running at full capacity with no downtime. The machine may stop and require operator attention with a Poisson arrival rate $1/\theta_m$. The parameter θ indexes reliability: in expectation, machines with higher θ run longer without operator intervention and produce higher expected output. When the machine is down, operator i can solve the problem and restart it with Poisson arrival rate h_i. More skilled operators (higher h_i) solve problems faster.

[14]These are important quality features of machines in the textile industry, among others, as we discuss in Section 2.

Let $\pi_1(t)$ denote the probability that the machine is running at time t and $\pi_0(t) = 1 - \pi_1(t)$ the probability that it is not. The states of the machine are governed by the Kolmogorov forward equation,

$$\dot{\pi}_1(t) = -\frac{1}{\theta_m}\pi_1(t) + h_i\pi_0(t).$$

The probability of the machine running decreases with the arrival of breakdowns and increases with the arrival of problem fixes. For any starting state of the machine and time t, this ordinary differential equation can be solved for the probability of the machine running.

We assume that the time period T relevant for worker assignment and wage setting is large enough so that the fraction of time the machine is running is equal to the steady-state probability,

$$\frac{1}{T}\int_{t=0}^{T}\pi_1(t)dt \approx \pi_1^*.$$

The steady-state probability is the solution to $-\frac{1}{\theta_m}\pi_1(t) + h_i\pi_0(t) = 0$,

$$\pi_1^* = \frac{\theta_m h_i}{1+\theta_m h_i}.$$

A worker i operating k units of a machine type m at firm j produces, in expectation,

$$F(A_m, k, \theta_m, h_i) = A_m k \frac{\theta_m h_i}{1+\theta_m h_i} \tag{1}$$

units of output. Full capacity output of k machines is $A_m k$. Downtime occurs in a $1/(1+\theta_m h_i)$ fraction of time. Again, because of T large, we abstract from randomness in the total output of the machine during a period of length T.

Are machine reliability and operator skill substitutes or complements in equation (1)? The marginal product of operator skill is

$$A_m k \frac{1}{\theta_m(h_i + 1/\theta_m)^2},$$

decreasing in machine reliability whenever

$$F_{\theta h} = -A_m k \frac{1 - 2/(1+\theta_m h_i)}{\theta_m^2(h_i + 1/\theta_m)^4} < 0.$$

This holds if and only if $\theta_m > 1/h_i$. This conditions means that the expected uptime of the machine exceeds the expected downtime, that is, the machine is running at least 50 percent of the time. In this case, the machine is running mostly independently and any increase in reliability decreases the need for operator attention.

1.2 The worker-level production function

A firm has a number of machines of each type, $\{K_m\}$ and a number of workers of each skill level $L(h)$. We assume that the number of workers is large enough so that there is always an operator available when a machine breaks down.[15] What is the optimal assignment of workers to machines?

[15] Obviously, this cannot hold with probability one unless $K < L$, in which case some workers would always sit idle. But, as Arrow et al. (1972, Section 4) show, the probability that all workers are busy fixing machines goes to zero when the number of both machines and workers grows without bound.

Denote by $k_m(h)$ the total number of type-m machines managed by workers with skill level h. Then the total expected output of the firm is

$$\sum_m \int_h F[A_m, k_m(h), \theta_m, h)]dh = \sum_m A_m \int_h k_m(h) \frac{\theta_m h}{1+\theta_m h} dh. \tag{2}$$

This is maximized with respect the resource constraints that (i) total operator attention time is equal to the working hours of each operator (normalized to one) times the number of operators with skill h,

$$\sum_m k_m(h) \frac{1}{1+\theta_m h} = L(h) \text{ for all } h, \tag{3}$$

and (ii) all machines are operated at full capacity,

$$\int_h k_m(h) dh = K_m \text{ for all } m. \tag{4}$$

This is a standard optimal transport problem (Galichon 2016) and can be characterized accordingly. The assignment should maximize output (2) subject to (3) and (4). We ignore any constraints of machine indivisibility and assume that $k_m(h)$ can be chosen continuously.

The first-order condition with respect to $k_m(h)$ is

$$A_m \frac{\theta_m h}{1+\theta_m h} - \lambda(h) \frac{1}{1+\theta_m h} - \mu_m \leq 0, \tag{5}$$

with equality whenever $k_m(h) > 0$. Here $\lambda(h)$ is the Lagrange multiplier associated with the time constraint of workers of skill h and μ_m is the Lagrange multiplier associated with the capacity constraint of machine m. Multiplying by $1 + \theta_m h$ and rearranging,

$$(A_m - \mu_m)\theta_m h \leq \lambda(h) + \mu_m.$$

In optimum, a worker with skill h will only operate one type of machine, for which the marginal product of her time (the left-hand-side) is the largest. All other machines will have lower marginal product and hence $k = 0$. This representation also follows from the Monge-Kantorovich duality of the problem.

For the optimally assigned machine, we have $k_m(h) = (1 + \theta_m h)L(h)$. Substituting into (1) and dividing by the number of type-h workers, the total output of worker h is

$$A_m \theta_m h. \tag{6}$$

This is the worker-level production function.

At the worker level, machine speed A_m, reliability θ_m and operator skill h are clearly complementary. The intuition for the complementarity with speed is that a given amount of downtime is more costly when the machine is fast. Skilled operators can better minimize downtime and avoid large output losses. The complementarity with reliability comes from the fact that reliable machines run for longer per unit of operator time. Hence a given operator can handle more of these machines in parallel. When juggling multiple machines, operator skill is more important.

1.3 Wage setting

We follow Card et al. (2018) and assume workers have upward-sloping labor supply curves at each potential employer firm due to idiosyncratic preferences. This results in monopsony power for the firm, which will pay a fraction of the value marginal product of the worker.

What is the marginal product of labor? It is the output that one more unit of operator time will yield to the firm, which is equal to the Lagrange multiplier $\lambda(h)$,

$$\lambda(h) = (A_m - \mu_m)\theta_m h - \mu_m.$$

Using equation (10) from Card et al. (2018), we can write wages as a weighted average of the worker i marginal product and her outside option b,

$$w_{ijm} = \beta(A_m - \mu_m)\theta_m h_i - \beta\mu_m + (1-\beta)b, \tag{7}$$

where $\beta \in (0,1)$ relates to the elasticty of labor supply. Appendix A derives this equation formally. We have normalized the output price to one (it can easily be subsumed into A_m).[16]

Proposition 1 *Wages are higher (i) on fast and reliable machines, (ii) on cheap machines, (iii) machine speed and reliability disproportionately favor skilled workers.*

Factor out $(1-\beta)b$, which captures a large share of of the wage relative to the marginal product, as evidenced by the small rent-sharing elasticities reported by Card et al. (2018). We can then use the $\ln(1+x) \approx x$ approximation and write

$$\ln w_{ijm} \approx \ln(1-\beta)b + \frac{\beta}{(1-\beta)b}(A_m - \mu_m)\theta_m h_i - \frac{\beta}{(1-\beta)b}\mu_m. \tag{8}$$

Suppose there are two types of machines, old ($m = 0$) and new ($m = 1$), with $A_1\theta_1 > A_0\theta_0$. The firm will assign old machines for all workers below skill level h_j^* and new machines above. This cutoff is determined implicitly by the condition that this marginal worker is equally productive on the two machines,

$$(A_1 - \mu_1)\theta_1 h_j^* - \mu_1 = (A_0 - \mu_0)\theta_0 h_j^* - \mu_0.$$

Let $\tilde{A}_m \equiv A_m - \mu_m$ and introduce the variable χ_{ij} as and indicator for $h_i > h_j^*$, that is, whether worker i is assigned to a new machine at firm j. The log wage rate of worker i at firm j is

$$\ln w_{ij} \approx \ln(1-\beta)b + \frac{\beta}{(1-\beta)b}\left[\tilde{A}_0\theta_0 h_i - \mu_0 + \chi_{ij}(\tilde{A}_1\theta_1 - \tilde{A}_0\theta_0)(h_i - h_j^*)\right] \tag{9}$$

We have used the definition of h_j^* as the skill at which the two machines are equally productive.

Equation (9) is our estimable wage equation. Wages depend on outside options (which will be captured by occupation-year fixed effects), machine productivity (captured by firm controls and fixed effects) and a return to skill. Note that the return to skill is higher when the worker uses a new machine $\chi_{ij} = 1$.

Figure 1 plots the wage function (ignoring constant parameter multipliers) for different levels of worker skill. Workers above skill level h_j^* will work on a new machine, be more productive and earn higher returns to skill.

[16] For tractability, we assume the outside option of the worker is exogenous and independent of skill. The working paper version of our paper (Koren & Csillag 2017) discusses the case when outside options are determined in a general equilibrium search model. The qualitative results remain the same.

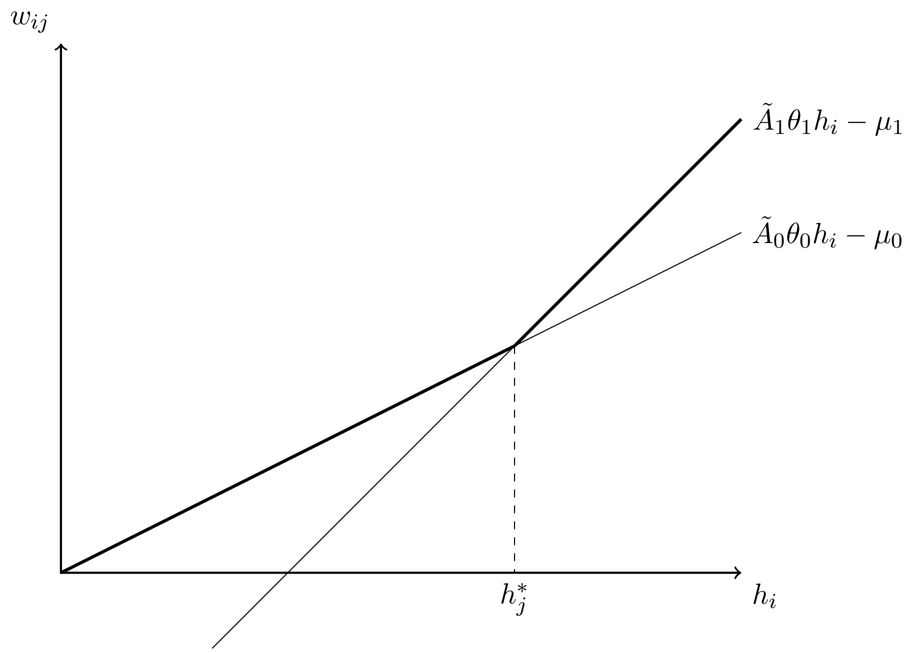


Figure 1: Machine assignment and wage setting by worker skill

Proposition 2 (Cross sectional patterns) *With optimal machine assignment across workers and monopsonistic wage setting,*

1. *conditional on machine productivity, wages increase in worker skill,*
2. *higher skilled workers are (weakly) more likely to use a new machine,*
3. *workers using a new machine earn higher wages,*
4. *the returns to skill are higher on new machines.*

1.4 Trade liberalization and technology upgrading

Suppose the (shadow) cost of new machines declines, because of, for example, trade liberalization. This results in the following effects.

Proposition 3 (Technology upgrading) *When μ_1 declines,*

1. *a larger fraction of operators within the firm uses a new machine,*
2. *workers switching to a new machine receive a wage increase,*
3. *the wage of all existing new machine users increases,*
4. *the returns to skill increase.*

Figure 2 illustrates these effects. The cutoff for using new machines shifts downward, and the wage of workers on new machines increases. The wage curve becomes weakly steeper. We will test these predictions in the following sections.

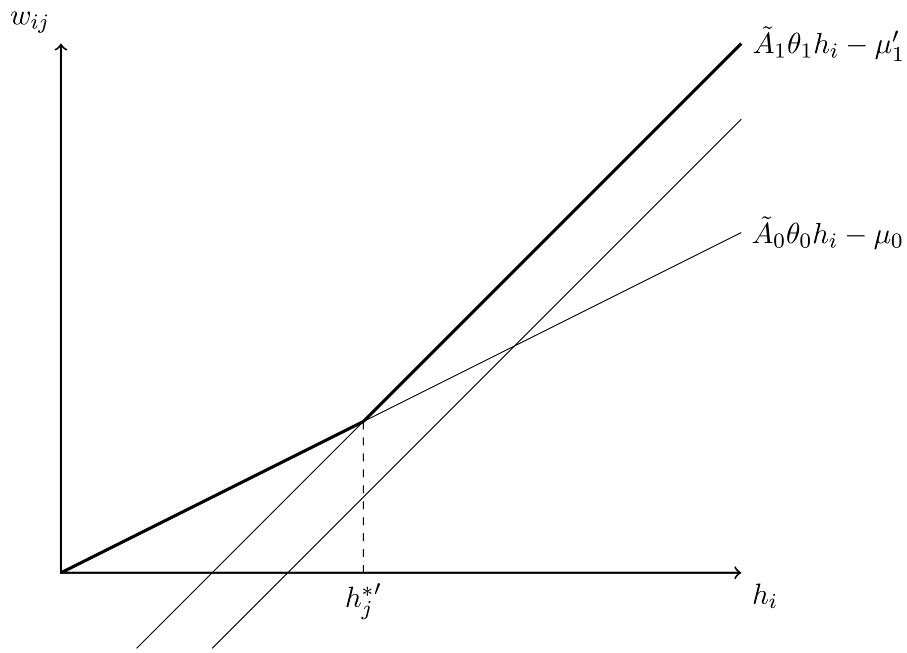


Figure 2: Technology upgrading by worker skill

2 A case study of a weaving mill

We briefly describe the case of an industrial plant undergoing profound technological change to illustrate the key predictions of the model presented in the previous section. The data come from a Hungarian cotton weaving mill, which operated Soviet and Czechoslovakian (STB and UTAS) weaving machines, together with a few oldish Swiss-made (shuttle Rüti) looms in 1988.

Starting with 1989, the first year of the post-communist transition, the plant dismounted three-quarter of its old machines and imported modern ones from Switzerland (Rüti F and G) and Japan (Toyota). From 1993, the plant operated an equal number of old and new machines (Figure 3).

We discuss several implications of this transformation using annual data on weavers (1988–95), and monthly data on machines (1991–97) and machine-worker matches (1991–95). The differences in coverage are explained by data availability, on the one hand, and wish to focus on the period after the plant's initial size reduction, on the other.[17]

Productivity and utilization of the old and new machines. Table 1 compares the old and new machines along a number of selected indicators. Each indicator is regressed on a "new machine" dummy and month fixed effects. We use panel data for five types of machines observed in a period of 75 months between May 1991 and August 1997.

The data suggests that new new machines are more productive (rows 1 and 2). The number of machines per worker is lower with the new machines (row 11), but this figure is misleading since the new looms are wider (have more warps per machine). The attended looms' potential output better approximates the size of the machinery to be operated by a weaver, which is significantly higher with new machines (row 3) The higher ratios of actual to potential output

[17]For a detailed case study on the plant (which did not address the questions asked here) see Köllő (2003).

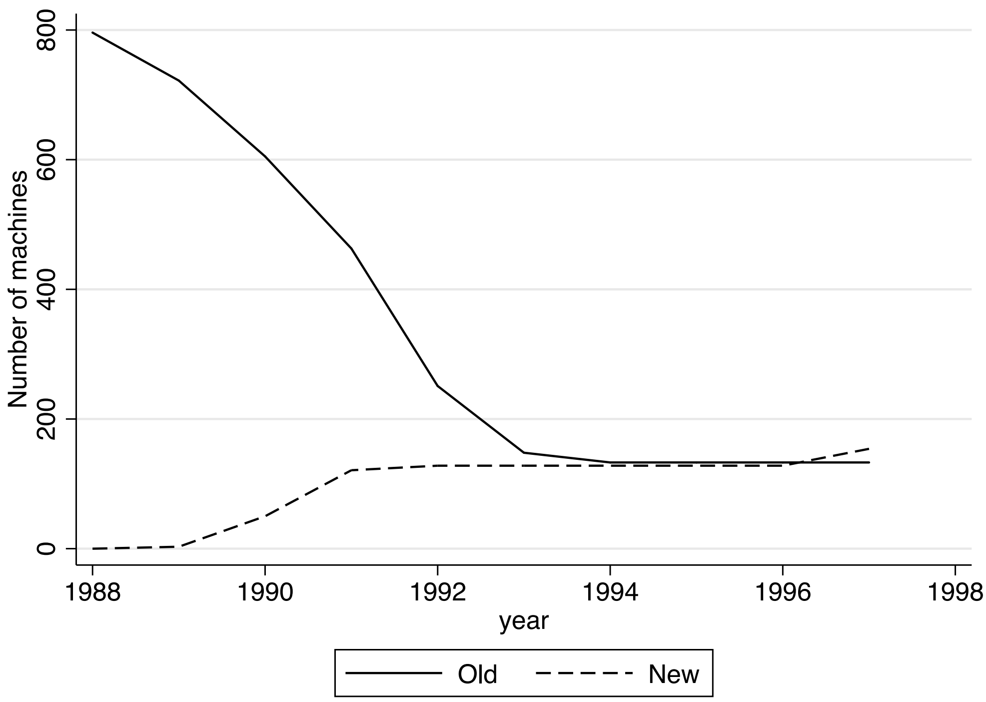


Figure 3: The number of old and new machines, 1988–1997

(row 4) suggests that total and operator-related downtime are slightly lower with the new looms. New machines are used to produce smaller batches of fabric to adjust to changing demand in the emerging market economy. The new machines lose more hours due to more frequent retooling (change of warp and weft), but this loss is offset by less time to be devoted to troubleshooting, repair and scheduled maintenance. The number of machines to be operated by weavers is set so that the number of required interventions per hour became roughly equal across old and new machines.

Assigning workers to machines. Table 2 addresses the question of how the probability of assigning a weaver to a new loom was affected by her estimated productivity. We approximate the latter with workers' within-loom residual wage under the piece rate scheme prevailing before 1990. We regress log wages in 1989 on age, age squared, a weekend shift dummy and type-of-machine fixed effects and took residuals.

In the second step, we estimate the effect of this individual-specific quality indicator on the probability that a continuing worker was matched to a new machine in or after 1990. We observe 519 person-years in 1990–1995 on the part of weavers, who also worked in the weaving mill prior to 1990. We find that the plant tended to match more productive weavers to new machines. Worker quality has a strong effect on the likelihood of assignment to a new machine.

Do workers gain from working with new machines? We address this question by means of a fixed effects panel wage regression relating log wages to age, age squared, a dummy for new machines, year effects and worker fixed effects to control for time-invariant personal attributes.

The results in Table 3 suggest that a shift from an old to a new machine is associated with a

Table 1: Differences between new and old machines—Regression estimates, 1991–1997

Dependent variable	Mean difference	Mean dep. var.	St. dev. dep. var.
Output (log)	0.820***	5.49	0.475
Potential output (log)	0.790***	5.94	0.449
Potential output/worker (log)	0.811***	3.52	0.845
Output/potential output (log)	0.031*	4.15	0.150
Percent downtime due to			
—scheduled maintenance	−3.20***	2.73	3.30
—troubleshooting	−1.68***	2.22	1.58
—change of warp	1.54**	8.33	5.97
—change of weft	0.940***	2.94	2.99
—other reasons	1.08	4.02	6.90
Total downtime	−0.961	20.38	9.74
Machine/worker	−2.64***	11.32	2.29
Interventions/hour	−1.64	45.26	9.46

Notes: Number of observations: 341 machine-months observed between May 1991 and August 1997. Estimation: OLS with robust standard errors. For an accounting of how the estimation sample was constructed see Appendix B. In each equation, the dependent variable is regressed on a dummy for new machines and month fixed effects. Coefficients significantly different from zero at 1, 5 and 10 percent are marked by ***, ** and *, respectively.

6 percent wage increase within individual workers' careers. (The ordinary least squares results are presented for comparison.)

Machine-level production function. Are there additional returns to worker skills on the new looms? We address this question by regressing log output by type of machine on the log number of workers, a dummy for new machines, the log residual wage of the continuing workers assigned to the given type of machine (as a measure of worker skill), and the interaction of the two latter variables (Table 4). We implicitly assume that the quality of continuing workers is positively correlated with the quality of those hired after 1989 (23 percent of all workers in 1995). We have 261 monthly observations from 1991–95.

First, the data suggests that worker quality, as measured here, exerts significant influence on the productivity of new looms while its effect is small and even negative in the case of old machines. Second, the productivity advantage of modern machines is enhanced by the average skills of the workers assigned to them.

All these predictions are consistent with the model predictions outlined in Propositions 2 and 3.

3 Data on other industries

To generalize our analysis to other industries, we use Hungarian linked employer-employee data from 1992–2004. In this time period, after the fall of communism in 1989 and before joining the European Union in 2004, Hungary witnessed rapid import liberalization. Motivated by our

Table 2: The effect of worker quality on the probability that a worker was matched to a new machine

	(1) Machine-worker assignment
Log residual wage in 1989	2.63***
	(0.645)
Age	0.231**
	(0.100)
Age squared	-0.004***
	(0.001)
Tenure (years)	0.051***
	(0.015)
Number of observations	519
Pseudo-R^2	0.233
Standard deviation of the residual wage	0.128
Mean dependent variable	0.299

Notes: Dependent variable: 1 if the worker is assigned to a new machine, and 0 otherwise. Sample: person-years for continuing workers employed in the plant in 1989. Estimation: Probit. The residual wage was measured by regressing log payments by results in 1989 on age, age squared and type of machine fixed effects. Standard errors (in parentheses) are calculated from a 200-repetition bootstrap. Coefficients significantly different from zero at 1, 5 and 10 percent are marked by ***, ** and *, respectively.

case study, we assume that imported machines represent newer technology than the existing machine stock of the country.[18]

Employee data comes 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 code, education, age and gender. We use the annual waves between 1992 and 2004. Earnings 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). In what follows, we refer to this latter track as "high school diploma."

We restrict our attention to 58 machine operator occupations, representing about 10 percent of the workforce in the private sector. We focus on producing sectors: agriculture, mining, manufacturing, construction and utilities. Results are similar if we narrow the sample to manufacturing sectors and occupations. Because sampling is different for small firms, we drop all

[18]We also conduct a more formal vintage analysis below.

Table 3: Wage gain from moving from an old to a new machine

	(1) OLS	(2) Worker FE
New machine	0.167***	0.060***
	(0.021)	(0.020)
Age	0.075***	0.187***
	(0.007)	(0.021)
Age squared	-0.001***	-0.001***
	(0.000)	(0.000)
Number of observations	1,595	1,595
Number of workers	579	579
R^2	0.818	0.872

Notes: Dependent variable: log hourly wage. Sample: Person-years for continuing workers employed in the plant in 1989. Standard errors, clustered by worker, are reported in parantheses. Coefficients signifiantly different from zero at 1, 5 and 10 percent are marked by ***, ** and *, respectively.

firms below 20 employees. We are left with 194,127 worker-year observations. We do not have individual identifiers for workers, so we cannot create a worker panel.

Each employer is matched to its Customs Statistics and Balance Sheet record based on a unique firm identifier. The Customs Statistics contain the universe of trading firms, recording their exports and imports in 6-digit Harmonized System (HS) product breakdown for all years from 1992 to 2003.[19] 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, we also see the specific equipment that it imported. We restrict our attention to 294 specialized machines and instruments that can be associated with a particular industry and occupation. 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 specialized machines.

The Balance Sheet of the firm has information on the book value of assets, including machinery, the average annual number of employees, and whether the firm is majority foreign owned. We use these as controls in our wage regressions. We also know when the firm was founded, and can control for firm age nonparameterically.

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

[19] Halpern, Koren & Szeidl (2015) provide more details on the Hungarian Customs Statistics dataset. Because the customs reporting rules change with EU accession in 2004, we cannot extend this analysis to later years.

Table 4: The effect of machine type and worker quality on log output per machine

	(1) Production function
Log number of weavers	0.109***
	(0.029)
New machine	-0.858**
	(0.335)
Log residual wage (as of 1989) of workers at the machine type	-9.91**
	(4.62)
New machine × log residual wage	38.53***
	(7.55)
Number of observations	261
R^2	0.733
Effect of the new machine at 25th percentile of the 1989 residual wage	-0.747
Effect of the new machine at 50th percentile of the 1989 residual wage	1.20
Effect of the new machine at 75th percentile of the 1989 residual wage	1.47

Notes: Dependent variable: log output per machine. Sample: machine-months for five types of loom. Estimation: OLS. The average residual wage was measured by regressing individual log annual earnings (based on payment by results) in 1989 on age, age squared and type of machine fixed effects, and averaging the residual for workers employed at the given type of machine in the given month. Output is measured in million pics/month. Standard errors (in parentheses) are calculated from a 200-repetition bootstrap. Coefficients significantly different from zero at 1, 5 and 10 percent are marked by ***, ** and *, respectively.

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 6.34 different type of machines, and the average machine is associated with 1.25 occupations. In the description of the FEOR classification, the Statistical Office advises on related but distinct occupations. For example, "type setter" is related to "printing machine operator." To allow for misclassification error both in survey responses and in our matching mechanism, we merge all related occupations. The Appendix provides the details of this matching procedure.

For each worker in each year, we create two measures of access to imported machinery. The first, M_{jt} is an indicator whether the firm j has imported any specialized equipment by year t. The second, χ_{jot} is an indicator whether this equipment is related to occupation o of the worker. By construction $M_{jt} \equiv \max_o \chi_{jot}$. We assumes that the effect of imported machines does not vanish over time.[20]

There are two potential sources of error with the measures M_{jt} and χ_{jot}. First, if some firms import capital indirectly, then we will classify some importers as nonimporters. This issue is

[20]We also experimented with a 5-year lifetime for imported machines as well as a 10 percent annual depreciation. Results were very similar.

not very severe for the specialized machines in our sample, for which only 22 percent of the total imports was purchased by intermediary firms (firms in the wholesale and retail sectors) in 1999, and the rest went directly to manufacturers.

Second, unlike in the case study, we do not know *which worker* within the specific occupation o 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. We explore this measurement error in more detail in Appendix B.

As we show in Appendix B, 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.

4 Patterns of imports and wages

4.1 Import trends

Table 5 shows the number of workers and firms in our estimation sample over time. Between about 17 and 57 percent of workers are exposed to imported machines, and this trend is clearly increasing over time. The third column reports the simple fraction of workers importing. Because the sampling rules change over time, this number is not representative of the overall import trends. The fourth column shows this number for a balanced sample, where firm-occupations are assigned constant weights. We see a dramatic increase in import exposure over the sample period.

How does importing relate to the general investment behavior of the firm? Although we did not include this in the model, the importing decision might also depend on the quantity of capital and its composition. In particular, imports may represent more recent vintages of equipment. We want to be able to separate the wage effect of imports from that of domestic investments.

We use annual data on the book value of machines and machine imports to construct a panel of machine purchases and a measure of vintages at the firm.[21] We first calculate nominal net investment flows for each firm for each year as the difference between the book value of equipment in consecutive years plus the amount of depreciation. If the net investment flow is positive, we treat it as gross investment (with zero disinvestment) into new vintages in that particular year. Similarly, if the net investment is negative, we treat it as pure disinvestment: the selling of the oldest possible vintage at the firm. Whenever imports are higher than net investment, we

[21] We face four data challenges in this exercise. First, while imports are detailed by product, domestic investments are not. Second, investments are recorded as net changes in asset values. That is, if a firm simultaneously purchases and sells a machine, only the difference in value is recorded. Third, we have to make assumptions when inferring the technological vintage of machines. We assume that purchased machines are new, whereas all sold machines are of the oldest possible vintage. Fourth, measurement errors may cause mismatches between data on domestic and imported investment. One source of error is if machine components are purchased as intermediate inputs rather than installed as capital. Another concerns the timing of purchase. An imported machine might only be installed one year later.

Table 5: The estimation sample over time

Year	Workers	Firms	Fraction importing (percent)	Import exposure (percent)
1992	10,853	1,823	35.27	16.57
1993	14,185	2,541	40.10	22.73
1994	14,695	2,773	39.07	27.26
1995	15,750	2,902	44.16	30.88
1996	15,419	2,775	48.74	34.35
1997	13,668	2,676	52.91	37.25
1998	15,239	2,754	55.22	40.04
1999	14,418	2,834	56.84	41.65
2000	14,805	2,966	55.89	43.44
2001	14,528	2,874	57.59	45.14
2002	15,907	2,345	53.40	45.99
2003	15,185	2,223	52.33	46.66
2004	15,261	2,281	49.86	46.66

Notes: "Fraction importing" denotes the fraction of workers in the sample in importer occupations and importer firms ($\chi_{jot} = 1$). "Import exposure" is defined on a balanced sample of firm-occupations and denotes the same importer fraction in this balanced sample.

infer that the firm concurrently installed new imported machines and sold equipment of an old vintage.

The result is a panel of gross investment and disinvestment flows by vintage (imputed year of purchase), separately for domestic and for imported machines. We cumulate these flows to construct a stock of vintages after deflating nominal flows by the overall machinery price index, separately for domestic and imported machines.

Table 6 presents the share of capital stock in each vintage for the year 2003. Capital stock is skewed towards later vintages, with a somewhat higher share coming from the first year of the sample.[22] The share of imports increases from 11 percent in the 1992 vintage to 75 percent in the 2003 vintage.

We next study how import behavior is correlated with tariffs. Tariffs on imported machinery have significantly declined in the 1990s. (See Table 7.) Hungary signed an Association Agreement with the European Economic Community (EEC) in 1991. This agreement stipulated the complete phaseout of tariffs on machinery (and other manufactures) from the EEC within ten years.[23] Given the small economic weight of Hungary relative to the EEC, we can think of these tariff changes as exogenous from the point of view of individual Hungarian producers.

We begin by creating occupation-specific tariff rates for each year, as the average of statutory tariff rate on machines associated with the occupation. For each machine, and hence for each occupation, we have a time series of tariff rates. We use tariffs on imports from the EEC (which

[22]The 1992 vintage includes all prior capital purchases.

[23]The agreement set three tariff cut schedules for three groups of industrial products. Each decreased tariffs linearly to zero, one by 1994, one by 1997, and one by 2001.

Table 6: The vintages of capital stock in 2003

Vintage	Machine stock (percent)	Imported (percent)
1992	1.73	10.92
1993	0.679	33.97
1994	0.948	43.93
1995	1.36	38.63
1996	1.58	40.17
1997	2.96	34.12
1998	3.96	43.92
1999	5.85	43.85
2000	8.73	41.37
2001	14.34	51.64
2002	19.84	62.95
2003	38.04	75.20

Notes: The second column reports the value share of various vintages in the total stock of machinery in 2003. The construction of machine vintage stocks is described in the main text. The third column reports the value share of imported machines within the vintage. All values are expressed in 2000 machinery prices.

Table 7: Average machinery tariffs

Year	Tariff on EU imports	Column 2 tariff
1992	9.40	9.70
1993	9.00	9.61
1994	8.69	9.61
1995	5.84	9.23
1996	3.18	9.02
1997	0.774	8.80
1998	0.572	8.56
1999	0.354	8.34
2000	0.176	8.33
2001	0.000	8.31
2002	0.000	8.33
2003	0.000	8.31

Notes: Table reports the unweighted average of tariffs on machinery imports from the European Economic Community (EU, second column), as well as the unweighted average of Column 2 tariffs on machinery (third column). Tariff rates are ad valorem percentages.

we call “EU tariffs”), as Column 2 tariffs were not significantly associated with machine imports.

Figure 4 plots the percentage point change in fraction of firms using imported machine within a given occupation against the percentage point change in EU import tariffs. Each dot represents an occupation in a three-year period. There is a negative association between tariff change and import adoption. Each percentage point reduction in tariffs from the EU is associated with a 1.24 percentage point increase in imports. We explore this relationship further in an instrumental variable strategy in Section 5.2.

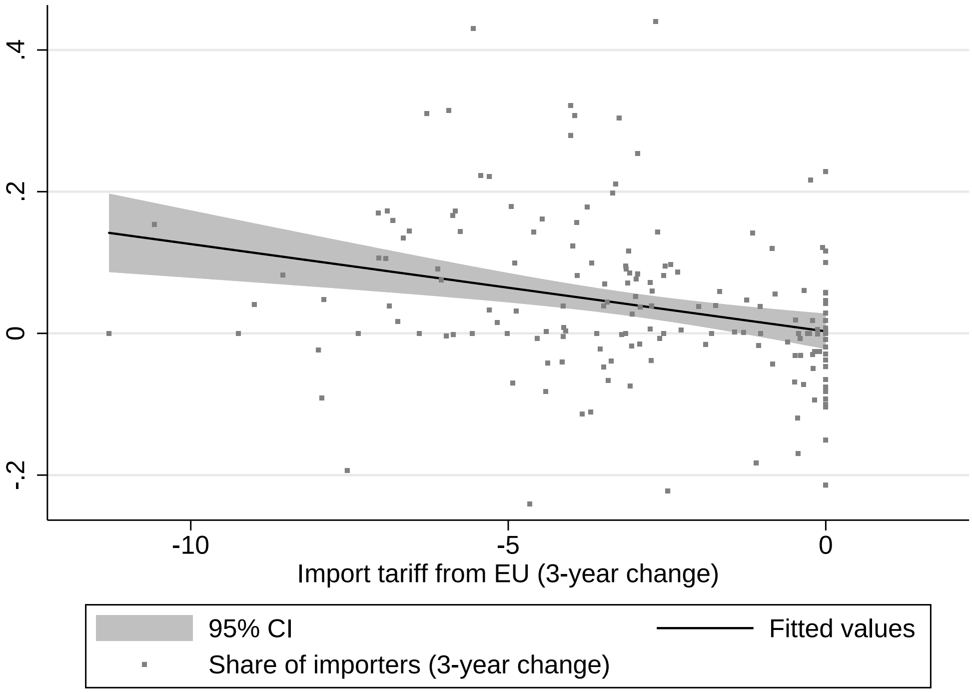


Figure 4: Occupations with faster tariff cuts adopt imported machines faster

4.2 Wages and the return to skill

Table 8 reports the the percentage wage gap between various groups of workers over time. The second column shows the percentage wage difference associated with a high-school degree (relative to primary school and vocational school), controlling for worker gender, age and occupation. The third column shows the percentage difference between the 90th and 10th percentile of the within-occupation wage distribution.

The minimum wage has increased in 2001 and 2002 by 96 percent in total, seriously compressing the lower end of the wage distribution. If we stop our analysis in 2000, we see that the return to a high school degree has increased from 18 percent to 23 percent. From 1992 to 2000, the wage gap between the 90th and the 10th percentile of the within-occupation wage distribution has widened from 168 percent to 228 percent. Between 2002 and 2004, the 90/10 wage dispersion continued to increase.

In what follows, we report inequality and return-to-skill numbers for the period 1992 to 2000. We let the years 1992–94 denote the "early" period and the years 1998–00 denote the "late" period.

To construct a model-consistent, continuous measure of skill, we study how wages are cor-

Table 8: Wage inequality over time

Year	High-school premium	90/10 inequality
1992	18.26	168
1993	17.51	179
1994	19.49	178
1995	18.22	176
1996	19.75	191
1997	20.24	219
1998	20.15	222
1999	22.85	221
2000	22.76	228
2001	18.07	198
2002	20.80	166
2003	15.39	180
2004	19.64	186

Notes: Table displays the percentage wage gap between various groups of workers over time. The second column shows the percentage wage difference associated with a high-school degree (relative to primary school and vocational school), controlling worker gender, age and occupation. The third column shows the percentage difference between the 90th and 10th percentile of the within-occupation wage distribution. The minimum wage has been raised by 96 percent between 2000 and 2002, significantly reducing both wage gaps.

related with worker observables. We first calculate the ranking of each worker in the wage distribution of their occupation in the given year. Let $p_{iot} \in [0, 1]$ denote the quantile of worker i in occupation o in year t. For the highest-paid worker in the occupation-year, $p_{iot} = 1$.[24] We then regress p_{iot} on time invariant worker observables X_i, separately for each year,

$$\hat{p}_{it} = E_t(p_{iot}|X_i). \tag{10}$$

These observables include the worker's gender, education, year of birth, occupation, and the interaction of all these indicators. The wage distribution changes year to year (for example, because of changes in the minimum wage), so we estimate the relationship between wage percentiles and worker observables separately for each year. Because the observables do not include firm-specific variables, the resulting measure of skill $\hat{p}_{it}$ does not depend on firm characteristics and wage policies. It takes values between 0 and 1, with higher values representing higher expected earnings.

We use the predicted quantile of the wage distribution, rather than the wage itself, to measure worker skill. This is because we want to study how the returns to skill changed over

[24] In practice, to correct for finite-sample bias, we set $p_{iot} = n_{ot}/(n_{ot} + 1)$, where n_{ot} is the number of workers in the occupation-year cell.

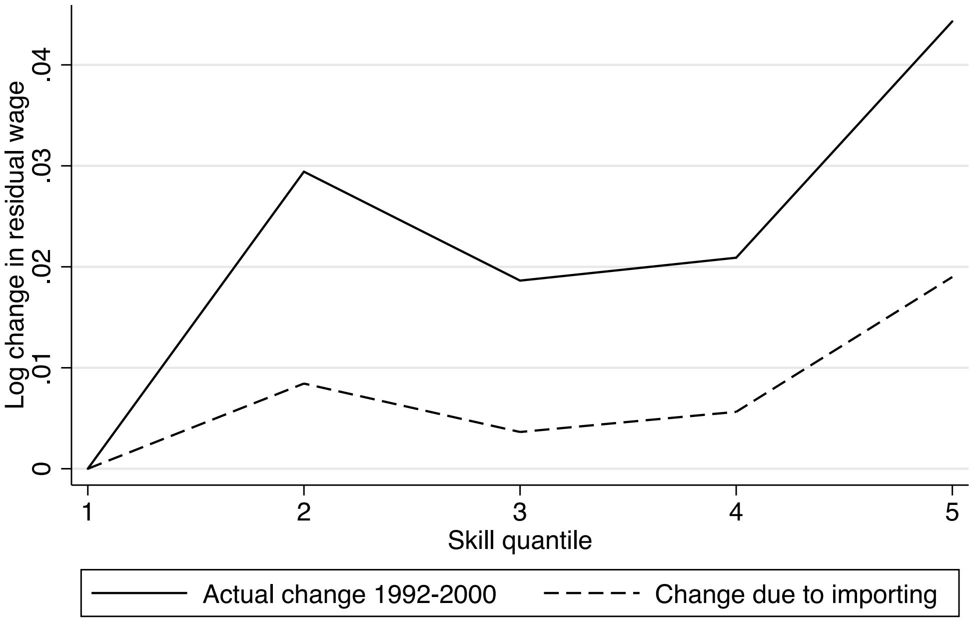
time. For example, we can compare the wages of workers with predicted quantiles 0.90 and 0.80 to estimate how the returns to skill have changed at the upper end of the distribution.

Specifically, we estimate the following wage equation.

$$\ln w_{ijot} = V_t(\hat{p}_{it}) + \alpha X_{jt} + \mu_o + \nu_t + u_{ijot} \tag{11}$$

The log earnings of worker i at firm j in occupation o in year t depends on a nonparameteric function of worker skill, firm observables, as well as occupation and year fixed effects. We let the function of skill depend arbitrarily on time. That is, we estimate a separate function for the early and the later period.

In practice, we estimate $V_t()$ at quintiles of $\hat{p}_{it}$. (Using splines of $\hat{p}_{it}$ or locally weighted regressions yields similar results.) The vector X_{jt} includes the log capital stock of the firm, indicators for majority foreign ownership and whether the firm has imported before, log machinery stock, log employment and a quadratic function of firm age.



Graph shows wage growth in quintiles of worker skill, conditional on firm obversables, occupation and year fixed effects. Residual wage growth for the lowest skill normalized to zero. Later years are omitted because of large raises in the minimum wage in 2001 and 2002.

Figure 5: Changes in the returns to unobserved skill

Figure 5 plots changes in our estimated V_t function. With a suitable normalization we set $\Delta V_t(0) = 0$, so that we can compare wages to workers with the lowest level of skill. We plot the log change in residual wages in each of the skill quintiles. Relative to the least skilled worker, the wage of the most skilled worker goes up by 4.53 percent between 1992 and 2000. This is accompanied by a "hollowing out" of the wage distribution, as the third and fourth quintiles do not grow as fast.

The figure also plots counterfactual changes in the returns to skill due to increased exposure to imported machines. As we discuss below, more skilled workers start importing earlier, and they receive a wage premium after importing. To estimate the combined trends in the correlation between importing and the returns to skill, we ask how the increased prevalence of imported machines within an occupation affect worker wages. We estimate a modified version of the returns to skill regression,

$$\ln w_{ijot} = V_0(\hat{p}_{it}) + V_1(\hat{p}_{it})M_{ot} + \alpha X_{jt} + \mu_o + \nu_t + u_{ijot}, \tag{12}$$

where M_{ot} is the fraction of workers exposed to an imported machine in occupation o in year t. The quantile function V_0 measures the returns to skill when no workers have access to imported machinery, whereas V_1 measures the marginal effect of import exposure by skill. The change in the returns to skill due to increased imports can be estimated as $V_1 \cdot \Delta M$.

Figure 5 plots the difference in return to skill for two values of import exposure. Low import exposure means that 24.87 percent of workers import in the occupation-year cell. This ratio corresponds to the weighted average of import exposure in 1992–94. High import exposure means 51.76 percent of workers importing, corresponding to the average of 1998–2000. The wage difference between the highest- and lowest-skill workers is 1.92 percent more under high than under low import exposure. This represents about 40 percent of the increase in the return to skill during our sample period.

4.3 When do firms import?

Table 5 showed that, over time, more and more workers are exposed to imports. We also saw in Table 6 that firms have increased the share of imported machinery in their capital stock. In this section we study the determinants of importing in more detail. We then develop an instrumental variable strategy based on exogenous declines in import tariff rates.

Let M_{jt} denote whether a firm j imports machinery in year t. We want to predict the first time of this happening, as the stock of machine will likely remain at the firm in later years. We hence need to model the hazard of *starting to import*.

We estimate a linear hazard model, where the hazard of starting to import depends on a hazard function ν_t and on firm controls:

$$\Pr(M_{jt} = 1 | M_{j,t-1} = 0) = \nu_t + \alpha X_{jt}. \tag{13}$$

The vector X_{jt} includes the log capital stock of the firm, its log employment, a quadratic function of its age, and an indicator whether the firm is majority foreign owned. We also add controls for the vintage composition of the firm's capital stock.

The first two columns of Table 9 report the results of two firm-year hazard regressions. In column 1, we let the hazard of importing depend on log capital stock, employment, foreign ownership, and other controls. We find that firms with more capital, more labor and foreign firms are more likely to start importing in any given year.

Column 2 controls for the vintage composition of the firm's capital stock. We capture this by the value share of equipment bought 2 to 5 years ago and the value share of equipment bought 6 or more years ago. The omitted category is newer equipment purchased within the past 1 year.

Vintages are associated with the hazard of importing in a non-monotonic way. A firm with 2–5 year-old machines is less likely to import. Firms with machines 6 years or older are more likely to import. This suggests that firms tend to replace older vintages of capital, but not recent

Table 9: When do firms start importing?

	(1) Hazard of importing	(2) Controlling for vintage	(3) Occupation level	(4) Tariff interactions
Book value of machinery	0.052***	0.053***	0.009***	0.005***
(log)	(0.006)	(0.006)	(0.000)	(0.000)
Employment	0.057***	0.055***	-0.002***	-0.003***
(log)	(0.010)	(0.010)	(0.001)	(0.001)
Foreign firm	0.312***	0.310***	0.056***	0.030***
(dummy)	(0.019)	(0.019)	(0.003)	(0.002)
Equipment bought 2–5		-0.112***		
years ago (share)		(0.028)		
Equipment bought 6 or		0.135		
more years ago (share)		(0.095)		
EU tariff × domestic firm				0.088***
× capital (log)				(0.012)
× employment (log)				0.069***
				(0.017)
EU tariff				0.605**
× foreign firm (dummy)				(0.253)
× capital (log)				0.193***
				(0.034)
× employment (log)				-0.108**
				(0.052)
Number of observations	32,843	32,843	156,914	156,914

Notes: The dependent variable is an indicator for importer status. All regressions estimate a linear probability model for the hazard of starting to import. Firm controls include quadratic functions of firm age. Columns 1 and 2 are estimated on a firm-year panel and control for year fixed effects. Columns 3 and 4 are esimtated on a firm-occupation-year panel and control for occupation-year fixed effects. Standard errors, clustered by firm, are reported in parantheses. Coefficients significantly different from zero at 1, 5 and 10 percent are marked by ***, ** and *, respectively.

ones. For simplicity, and because we have a very rudimentary estimate of capital vintage, our model does not capture the dynamic nature of machinery choice.

Columns 3 and 4 report regressions at the firm-occupation-year level. Column 3 only reestimates specification 1 at the firm-occupation-year level. Note that some of the variation in import behavior is soaked up by occupation-year effects, so the marginal effects of our explanatory variables are smaller.

In Column 4, we control for the level of tariffs. We calculate the relevant tariff as the average tariff facing EU imports for machines relevant to the given occupation in the given year.[25] Given the occupation-specific tariff rates, we can also calculate tariff rates for non-importers, because we observe the precise occupation of their machine operators. This way we can construct a relevant tariff rate for each occupation within each firm in each year.

The model predicts that lower tariffs are associated with a higher hazard of importing. This effect, however, may be heterogeneous across firms (Halpern et al. 2015). We hence interact tariff rates with log capital stock, log firm employment and a foreign owner indicator to predict which firms will start importing.

More specifically, we augment our hazard model to depend on an occupation-specific hazard function ν_{ot} and on tariffs τ_{ot}^{EU}, interacted with firm size and foreign ownership:

$$\begin{aligned}\Pr(\chi_{jot} = 1|\chi_{jo,t-1} = 0) = \nu_{ot} + \alpha X_{jt} \\ + \tau_{ot}^{\mathrm{EU}}[\gamma_0 + \gamma_1(1 - F_{jt}) \ln K_{jt} + \gamma_2(1 - F_{jt}) \ln L_{jt} \\ + \gamma_3 F_{jt} + \gamma_4 F_{jt} \ln K_{jt} + \gamma_5 F_{jt} \ln L_{jt}]. \quad (14)\end{aligned}$$

Note that γ_0, the direct effect of tariffs, cannot be identified separately from ν_{ot}, so we assume it to be zero. In practice, it will be soaked by occupation-year fixed effects. The identification of γ_1 through γ_5 comes from whether large firms respond more to tariffs than small ones, estimated separately for domestic and foreign firms.

Column 4 of Table 9 reports the estimated γ coeffients from the hazard model. We find $\gamma_1 > 0$ and $\gamma_2 > 0$. That is, among domestic firms, tariffs have a stronger negative effect on the imports of firms that are small in terms of capital and employment. Among foreign firms, tarrifs have a weaker negative effect ($\gamma_3 > 0$), especially for firms with few workers ($\gamma_4 < 0$) and much capital ($\gamma_5 > 0$). This is perhaps not surprising, given their better access to foreign markets (Halpern et al. 2015). The exclusion test of these tariff interactions yield an F-value of 86.55.

4.4 Which workers import?

We then ask which workers import within an occupation. Proposition 2 states that workers with higher skill are more likely to import. To test this prediction, we study when a firm-occupation cell first imports a machine. If this cell comprises of higher-skilled workers, it should start importing sooner.

We use the skill index for each worker based on their observed characteristics, as defined above. We then group these workers into three categories. Early importers are those whose firm has first imported their related machine in 1996 or earlier. Late importers are every other importer. The remaining workers are non-importers, or "never" importers.

Figure 6 displays the frequency of these three categories for each skill quintile. Consistently with the model, early importers are overrepresented among high-skilled workers. Late importers have a balanced distribution of skill, whereas workers that never import tend to be of a lower skill.

[25] Column 2 tariffs were not significantly correlated with importing.

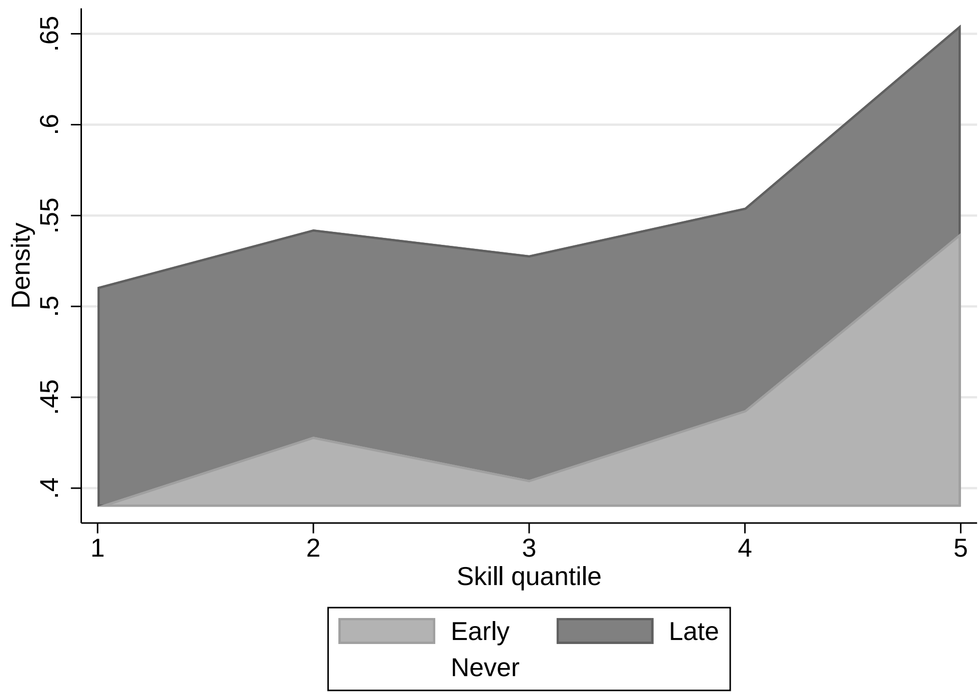


Figure 6: Among high-skill workers, early importers are overrepresented

5 The effect of import exposure on wages

In this section we estimate the effect of imported machines on wages.

5.1 Implementation

Recall our estimable wage equation from (9)

$$\ln w_{ij} \approx \ln(1-\beta)b + \frac{\beta}{(1-\beta)b}\left[\tilde{A}_0\theta_0 h_i - \mu_0 + \chi_{ij}(\tilde{A}_1\theta_1 - \tilde{A}_0\theta_0)(h_i - h_j^*)\right]. \quad (9)$$

We map this to the available data as follows.

$$\ln w_{ijot} = \nu_{ot} + \nu_{jt} + \gamma_h h_i + \gamma_\chi \chi_{jot} + \gamma_{\chi h}\chi_{jot} h_i + u_{ijot}. \quad (15)$$

where $\ln w_{ijot}$ is the log monthly earnings of worker i at firm j in occupation o in year t, χ_{jot} is an indicator taking the value one if the firm has imported the machine necessary for occupation o by time t.

The occupation-time fixed effect ν_{ot} and firm controls (including, in some specifications, firm-time fixed effects ν_{jt}) capture variation in outside options of workers b and the productivity and the shadow cost of domestic machines A_0 and μ_0.

We are interested in the coefficients γ_χ, measuring the wage effect of importing, and $\gamma_{\chi h}$ measuring the changing returns to skill on imported machines. We expect both to be positive. Our measure of skill is an indicator whether the worker has a high school diploma. The coefficient $\gamma_{\chi h}$ corresponds to the productivity premium of imported machines in the model, $(\tilde{A}_1\theta_1 - \tilde{A}_0\theta_0)b\beta/(1-\beta)$. This can be compared to the returns to skill on domestic machines

$\gamma_h = \tilde{A}_0\theta_0 b\beta/(1-\beta)$. Hence $\gamma_{\chi h}/\gamma_h$ measures the proportional increase in returns to skill on imported machines.

In addition to these model-implied determinants of wages, we always control for the education, gender and age (in quadratic form) of the worker, and the capital stock, employment, foreign ownership, past import experience and age (in quadratic form) of the firm. Note that import experience does not explain all the variation in χ_{jot}, because this latter also varies across occupations.

Table 10 reports the estimated treatment effects together with standard errors clustered by firm. The baseline specification in Column 1 yields an estimate γ_χ of 0.048, which means that workers exposed to imported machines earn 4.94 percent more than similar workers at similar firms using only domestic machines.

Among firm controls, foreign ownership and capital stock are strongly associated with wages. Foreign firms and firms with more machinery pay higher wages. Note that machinery is measured in value, so more expensive machines are also found to be associated with higher wages. The exposure to imports implies an additional wage premium, over and above the potentially higher value of machinery stock. This suggests that operator wages rise not only in the quantity, but also in the quality of machines, as predicted by the model.

In Column 2, we include firm-year fixed effects to control for unobserved, time varying firm characteristics that may affect both importing and wages. The wage premium of imported machines is 3.10 percent.[26]

We discuss instrumental variables estimates below.

Table 11 shows the estimated skill premium for three groups of workers. We estimate the difference in log wages between workers with and without a high school diploma, conditional on controls. The first row reports the high school premium among workers at non-importer firms. These firms have not imported any machinery. The second row reports the high school premium for workers in non-importer occupations at importer firms. Finally, the third row reports the high school premium for workers in importer occupations at importer firms. For brevity, we do not report the coefficients of other controls.

As Column 1 shows, the skill premium among non-importers is 10.53 percent. At importer firms, the premium is 13.54 and 13.71 percent for non-importer and importer occupations, respectively. That is, the high school premium is higher at importer firms. In Column 2, we include firm-year fixed effects to control for time varying firm unobservables. The gap between non-importers and importers is even bigger.

In all specifications (see our discussion of instrumental regressions below), the returns to a high school diploma is highest for importer occupations at importer firms. The difference relative to non-importers is statistically significant, whereas the difference relative to non-importer occupations at importer firms is insignificant. Notice that we can estimate the group-specific returns to skill less precisely than the overall returns to skill, because there are few workers at importer firms who work in non-importer occupations. By our most conservative estimates, compared to domestic machines, imported machines raise the returns to skill by 28.30 percent.

[26]The estimated wage returns to being exposed to foreign machines are slightly lower than the returns to computer use, as reported by Spitz-Oener (2008) and Dostie et al. (2010).

Table 10: The effect of import exposure on wages

	(1) Baseline	(2) Firm-year	(3) IV	(4) IV FE
Importer occupation	0.048***	0.031***	0.578***	0.034
at importer firm (dummy)	(0.010)	(0.007)	(0.101)	(0.032)
Importer firm	0.006		0.155	
(dummy)	(0.010)		(0.093)	
High school diploma	0.123***	0.090***	0.110***	0.092***
(dummy)	(0.007)	(0.007)	(0.008)	(0.007)
Foreign firm	0.161***		0.034	
(dummy)	(0.013)		(0.026)	
Book value of machinery	0.067***		0.033***	
(log)	(0.005)		(0.007)	
R^2	0.479	0.157		
Number of observations	189,913	189,913	189,913	170,416
F-test for 1st stage			52.58	104

Notes: The dependent variable is the log monthly earning of the worker in the given year. All specifications control for occupation-year fixed effects. Worker controls include indicators for gender and schooling and a quadratic function of worker age. Firm controls include log capital, log employment and a quadratic function of firm age. In columns 3 and 4, worker exposure to imported machine is instrumented with the predicted probability to import for the given occupation and the firm as a whole. Standard errors, clustered by firm, are reported in parantheses. In columns 3 and 4, standard errors and p-values are calculated from a 200 repetition bootstrap. Coefficients significantly different from zero at 1, 5 and 10 percent are marked by ***, ** and *, respectively.

5.2 Instrumenting imports with tariffs

To identify the causal effect of importing on wages, we need exogenous variation in firm import behavior. We follow Goldberg, Khandelwal, Pavcnik & Topalova (2010) and Kasahara et al. (2016), and exploit a large trade liberalization episode, namely, Hungary's accession to the EU. As described in Section 4.1, tariffs on machinery (and all industrial goods) have been gradually phased out between 1992 and 2001. Tariff rates were different at the beginning of the sample and the phase-out happened at different speeds, creating variation in product-level tariff rates.

Our key explanatory variable is defined at the firm-occupation-year level: whether firm j has already imported a machine specific to occupation o by year t. To generate exogenous variation at the firm-occupation-year level, we turn to the hazard regression described in equation (14).

Taking the predicted value from equation (14) as

$$\hat{\zeta}_{jot} \equiv \hat{\nu}_{ot} + \tau_{ot}^{\mathrm{EU}}[\hat{\gamma}_1(1-F_{jt})\ln K_{jt} + \hat{\gamma}_2(1-F_{jt})\ln L_{jt} + \hat{\gamma}_3 F_{jt} + \hat{\gamma}_4 F_{jt}\ln K_{jt} + \hat{\gamma}_5 F_{jt}\ln L_{jt}]$$

we have an estimated hazard of importing. We then calculate the predicted probability of a

Table 11: High school wage premium by import exposure

	(1) Baseline	(2) Firm-year	(3) IV	(4) IV FE
Non-importer firm	0.100***	0.057***	0.024	0.031***
	(0.012)	(0.008)	(0.033)	(0.016)
Non-importer occupation	0.127***	0.082***	0.119***	0.098***
at importer firm	(0.010)	(0.009)	(0.037)	(0.022)
Importer occupation	0.128***	0.101***	0.134***	0.106***
at importer firm	(0.010)	(0.009)	(0.016)	(0.013)
R^2	0.479	0.157		
Number of observations	189,913	189,913	189,913	170,416

Notes: The table reports the returns to high school degree in three groups of workers. The dependent variable is the log monthly earning of the worker in the given year. All specifications control for occupation-year fixed effects. Worker controls include indicators for gender and schooling, a quadratic function of worker age and indicators for importer status. Firm controls include log capital, log employment, a quadratic function of firm age and an indicator for whether the firm is an importer. In columns 3 and 4, worker exposure to imported machine is instrumented with the predicted probability to import for the given occupation and the firm as a whole. Standard errors, clustered by firm, are reported in parantheses. In columns 3 and 4, standard errors and p-values are calculated from a 200 repetition bootstrap. Coefficients significantly different from zero at 1, 5 and 10 percent are marked by ***, ** and *, respectively.

firm having imported by time t as

$$\hat{\pi}_{jot} = 1 - \prod_{s=b_j}^{t} (1 - \hat{\zeta}_{jos}),$$

where b_j is the first year of the firm in the data. The probability of importing in the first years of a firm's life is just one minus the probability that it did not import in any of those years. Because EU tariffs are exogenous from the firm's point of view, we can use $\hat{\pi}_{jot}$ as an instrument for χ_{jot}. We similarly construct an instrument for firm-level imports. Because $\hat{\pi}_{jot}$ is increasing in the firm's age, we control for a quadratic function of firm age in all regressions.

Table 12 reports the first stage of a two-stage least squares regression. Using the predicted probability of importing as an instrument for actual importing yields a strongly significant first stage at the firm-occupation level, with an F-test of 52.58. The association is similarly strong at the firm-level. That is, our instruments generate sufficient variation in both the firm-occupation- and the firm-level import indicator.

As Column 3 of Table 10 shows, the IV estimate of the effect of imported machine on operator wages is 0.578. This is larger than the OLS estimate reported in Column 1, suggesting that the negative bias from measurement error is larger than the positive bias from firm selection.

In Column 4, we include firm-year fixed effects in both the first and second stages of the

Table 12: Predicted and actual importing

	(1) Firm-occupation import	(2) Firm import	(3) Firm-occupation import FE
Predicted probability of	0.638^{***}	0.127^{***}	1.72^{***}
firm-occupation importing	(0.069)	(0.055)	(0.162)
Predicted probability of	-0.087^{**}	0.304^{***}	
firm importing	(0.038)	(0.036)	
Book value of machinery	0.033^{***}	0.033^{***}	
(log)	(0.005)	(0.004)	
Firm is foreign owned	0.094^{***}	0.076^{***}	
(dummy)	(0.020)	(0.014)	
R^2	0.432	0.391	0.801
Partial F-test	52.58	61.06	104
Number of observations	189,913	189,913	170,416

Notes: The dependent variable is an indicator for importer status. All regressions estimated by ordinary least squares and control for firm-year and occupation-year fixed effects. Worker controls include indicators for gender and schooling and a quadratic function of worker age. Standard errors, clustered by firm, and calculated from a 200 repetition bootstrap, are reported in parantheses. Coefficients significantly different from zero at 1, 5 and 10 percent are marked by ***, ** and *, respectively.

regression. The number of observations is lower than in other specifications, because with firm fixed effects, we cannot estimate the hazard models for firms that start importing in their first year. (They have only one period of observation in the hazard estimate.) The wage premium associated with importing is 3.46 percent (not statistically significant).

In addition, as Columns 3 and 4 of Table 11 show, the returns to skill increase in firm-occupations that are induced to import by tariff reductions.

5.3 Robustness

Table 13 reports the results of wage regressions with various number of firm controls. Column 1 report a specification with only worker controls and no firm controls at all. In this specification, we are comparing the wages of importer workers to those of similar non-importer workers. Workers at importing firms earn 18.69 percent more than similar workers at non-importing firms. If the imported machine is specific to their occupation, they earn an additional 18.92 percent more. As we see below, most of these large differences can be attributed to the selection of firms into importing.

To control for the quantity of capital, Column 2 includes the log capital stock of the firm. Indeed firms with more capital pay higher wages. The wage premium of importing workers drops to 9.05 percent and the wage premium of importing firms reduces even further.

In Column 3, we control for not only the quantity, but also the vintage of capital stock. We include the shares of capital vintages between 2 and 5 years and those that are older than

Table 13: Robustness to various firm controls

	(1) No firm controls	(2) Capital stock	(3) Vintage	(4) Full controls
Importer occupation	0.173***	0.087***	0.085***	0.049***
at importer firm (dummy)	(0.016)	(0.012)	(0.012)	(0.011)
Importer firm	0.171***	0.033***	0.033**	0.016
(dummy)	(0.014)	(0.013)	(0.013)	(0.013)
Book value of machinery		0.072***	0.072***	0.073***
(log)		(0.004)	(0.004)	(0.005)
Equipment bought 2–5			-0.051***	-0.040***
years ago (share)			(0.015)	(0.015)
Equipment bought 6 or			0.056	0.036
more years ago (share)			(0.041)	(0.046)
Foreign firm				0.158***
(dummy)				(0.014)
R^2	0.410	0.480	0.481	0.503
Number of observations	121,225	121,225	121,225	121,225

Notes: The dependent variable is the log monthly earning of the worker in the given year. All specifications control for occupation-year fixed effects. Worker controls include indicators for gender and schooling and a quadratic function of worker age. In column 4, full controls include log employment and firm age (not reported). Standard errors, clustered by firm, are reported in parantheses. Coefficients significantly different from zero at 1, 5 and 10 percent are marked by ***, ** and *, respectively.

6 years. The omitted category is more recent vintages. The estimated wage premium barely changes.

In Column 4, we include the full set of firm controls we used in our main specification, including capital stock, an indicator for foreign ownership, log employment and age (not reported). We also include the vintage composition of capital. The estimated wage premium drops to 5.00 percent, but is still strongly significant.

Appendix B contains further robustness checks.

6 Conclusions

We showed in Hungarian linked employer-employee data for 1992-2004 that machine operators exposed to imported machines earn higher wages than similar workers at similar firms. The wage import premium only applies to occupations related to the specific machine imported by the firm. Using product-specific tariff rates as instruments for importing suggests that the importer wage premium is causal. The returns to skill have increased in our sample between 1992 and 2000. About 40 percent of the increase can be attributed to greater exposure to imported machines. We built a model to explain which workers use imported machines and how this affects wages. Our results suggests that imported machines can help propagate skill-biased technical change.

We see a number of directions for future research. First, to further explore how trade affects workers, our measure of import exposure could be extended to other products and other occupations beyond machines and machine operators. Obtaining a better exposure measure is important because, as Hummels et al. (2014) document, the wage effects of offshoring are heterogenous across workers.

Second, the dynamic nature of the decision to import could be studied in more detail. We have shown that firms with recent investments are less likely to import a machine than firms with older vintages. The cross-firm variation in vintages could help explain the cross-firm inequality in wages (Hornstein, Krusell & Violante 2002).

Third, the skill-biased nature of imported machines could be endogenized in a model of directed technical change (Acemoglu 1998, Acemoglu 2002) and appropriate technology (Basu & Weil 1998). As Caselli & Wilson (2004) document, countries import equipment that are complementary to their existing composition of workers. A more complete model could link trade in capital goods, skill premia, and productivity differences across countries.

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A Appendix A: Derivation of the wage equation

Recall the revenue of the firm from equation (2),

$$\sum_m \int_h F[A_m, k_m(h), \theta_m, h)]dh = \sum_m A_m \int_h k_m(h) \frac{\theta_m h}{1+\theta_m h} dh. \tag{2}$$

Suppose the firm post wages $w(h)$ for workers of skill h, facing an upward sloping supply function,

$$L(h) = \bar{L}(h)\,[w(h) - b]^{\gamma} \ \text{ for all } h. \tag{16}$$

The demand for total operator time is equal to,

$$\sum_m k_m(h) \frac{1}{1+\theta_m h} = \bar{L}(h)\,[w(h) - b]^{\gamma} \ \text{ for all } h. \tag{17}$$

All machines are operated at full capacity,

$$\int_h k_m(h)dh = K_m \text{ for all } m. \tag{4}$$

The firm maximizes (2) minus wage bill $\int_h w(h) \sum_m k_m(h) \frac{1}{1+\theta_m h} dh$ with respect to $k_m(h) \geq 0$ and $w(h) \geq 0$.

The first-order condition with respect to $k_m(h)$ is

$$A_m \frac{\theta_m h}{1+\theta_m h} - [w(h) + \lambda(h)] \frac{1}{1+\theta_m h} - \mu_m \leq 0, \tag{5}$$

with $\lambda(h)$ being the Lagrange multiplier associated with the constraint (17) and μ_m is the Lagrange multiplier of (4).

The first-order condition with respect to $w(h)$ is

$$-\sum_m k_m(h) \frac{1}{1+\theta_m h} + \lambda(h)\gamma \bar{L}(h)[w(h) - b]^{\gamma-1} = 0. \tag{18}$$

Substituting into (17),

$$\lambda(h) = \gamma[w(h) - b],$$

and

$$A_m \frac{\theta_m h}{1+\theta_m h} - [(1+\gamma)w(h) - \gamma b] \frac{1}{1+\theta_m h} - \mu_m \leq 0.$$

For the range of skills for which $k_m(h) > 0$, the above condition holds with equality and we can express wages as

$$w(h) = \frac{\gamma}{1+\gamma} b + \frac{1}{1+\gamma} \left[(A_m - \mu_m)\theta_m h - \mu_m \right]. \tag{19}$$

This is the same as equation (7) with $\beta = 1/(1+\gamma)$.

B Appendix B: Dealing with measurement error in machine assignment

In the data we can only assign machines to occupations, not to workers. Hence if a firm imports a machine, we will assign it to all the workers in the affected occupation. This introduces a measurement error, because some of the workers in this occupation will continue to work on domestic machines. This error biases the estimated effect of imported machines towards zero. In this Appendix we derive the magnitude of this bias and develop methods for correcting it.

For simplicity, assume that the true wage equation is

$$w_{ijot} = \xi \chi_{ijot} + \varepsilon_{ijot}, \tag{20}$$

where χ_{ijot} is the true importer status of a worker i at firm j in occupation o in year t and ε_{ijot} is an orthogonal error term. If we observed χ_{ijot}, we could estimate (20) by simply regressing wages on the importer dummy and would get a consistent estimate of ξ.[27]

[27] In this discussion of measurement error, we simply ignore the issue of endogeneity. We have discussed that at length in Section 5.2.

However, we only observe

$$\chi_{jot} = \max_i \chi_{ijot}$$

and estimate

$$w_{ijot} = b\chi_{jot} + \varepsilon_{ijot}. \tag{21}$$

The OLS estimate of b is the mean difference of wages between individuals with $\chi_{jot} = 1$ and with $\chi_{jot} = 0$,

$$\operatorname{plim} \hat{b}_{OLS} = \mathrm{E}\left(w_{ijot}|\chi_{jot} = 1\right) - \mathrm{E}\left(w_{ijot}|\chi_{jot} = 0\right) = \xi \Pr(\chi_{ijot} = 1|\chi_{jot} = 1) < \xi. \tag{22}$$

The fewer the true importers among classified importers, the stronger the bias towards zero.

When we include firm fixed effects in (21), the estimate of b becomes

$$\hat{b}_{FE} = \frac{\sum_{jt}(\bar{w}_{1ft} - \bar{w}_{0ft})n_{0ft}n_{1ft}/n_{jt}}{\sum_{jt} n_{0ft}n_{1ft}/n_{jt}}, \tag{23}$$

where $\bar{w}_{1ft}$ is the average wage in firm j in year t for workers with $\chi_{jot} = 1$. Similarly, $\bar{w}_{0ft}$ is the average wage for $\chi_{jot} = 0$. The number of such workers are n_{1ft} and n_{0ft}, respectively.

The fixed-effect estimate of the wage difference is a weighted average of within-firm wage differences, with the weight depending both on the number of workers at the firm (n_{jt}) and the share of observed importers at the firm (n_{1ft}/n_{jt}). Otherwise, the bias in $(\bar{w}_{1ft} - \bar{w}_{0ft})$ is the same.

$$\operatorname{plim} \hat{b}_{FE} = \xi \frac{\sum_{jt} \Pr(\chi_{ijot} = 1|\chi_{jot} = 1)n_{0ft}n_{1ft}/n_{jt}}{\sum_{jt} n_{0ft}n_{1ft}/n_{jt}} < \xi. \tag{24}$$

To quantify the bias, assume that each worker indepently imports with a probability q. Then

$$\Pr(\chi_{ijot} = 1|\chi_{jot} = 1) = \frac{q}{1 - (1 - q)^{n_{1fot}}}.$$

For small $q \approx 0$, this can be approximated as $1/n_{1fot}$. When there are many workers in the affected occupation, it is difficult to tell which one received the imported machine, and the estimated wage premium of importing is biased towards zero.

Using this approximation, we calculate that the average bias factor for the OLS equation is 0.188. For the firm-year fixed effects specification, the average bias factor is 0.143. Both of these are much less than 1, suggesting that the bias is pervasive.

We address this bias in a number of ways. First, we weight all observations by $1/n_{jot}$ to underweight observations where the bias would be large. This is equivalent to estimating the regression at the firm-occupation-year level, rather than the worker-year level. Column 1 if Table 14 reports the results of the weighted regression. The effect of imports on wages are estimated to be somewhat larger than the unweighted estimate in Table 10.

Second, we exclude firm-occupation-year cells with more than 20 workers. Given the 6 percent sampling probability, such firm-occupation-year cells represent about 300 workers. It would be hard to tell who gets an imported machine at such a large firm. This specification is reported in column 2 of Table 14. The import effect is strongly positive.

Third, we estimate the coefficient of a modified import exposure variable, which takes the value 0 if the firm-occupation does not import and the value $1/n_{jot}$ if it does. This way, we are not excluding large occupations, but expect the treatment effect in these to be smaller. Column

3 of Table 14 reports the results, which are similar to the previous estimates. One issue with this method is that large firm-occupations may buy multiple machines, resulting in a larger than expected treatment effect. We control for this possibility in our fourth specification.

Fourth, we construct a more precise index of import exposure by calculating the value of imported machines per worker. We first cumulate import spendings over time (deflated by the price index of imported equipment) to obtain a stock of imported equipment at each firm. We do this spearately for each 6-digit product. Because each machine can potentially be used by multiple machine operators, we divide the stock of the machine value by the number of relevant machine operators at the firm. For each worker, we add the stock of all 6-digit machines that, according to her occupation code, she can operate. This is a continuous measure of specific imports per worker, amounting to 4.32 million Ft for the median worker.

We also create a measure of total imports per worker, which includes the value of all specialized imported equipment at the firm, whether or not they are related to the worker's specific occupation. This is our measure of generic imports.

To attenuate measurement error, we divide both measures of import per worker into quartiles, and estimate the wage differences across workers in different quartiles. The wage equation becomes

$$w_{ijot} = \sum_{m=1}^{4} \xi^{(m)} S_{jot}^{(m)} + +\alpha X_{jt} + u_{ijot}. \tag{25}$$

Relative to the baseline category of non-importers, workers in the lowest quartile of specific imports earn $\xi^{(1)}$ higher wages. We anticipate this wage premium to be higher in higher quartiles.

Column 4 of Table 14 reports the results. Workers in firm-occupations in the first (smallest) quartile of import per worker receive wages that are not significantly different from non-importers. Wages are continuously increasing with import exposure. The third quartile is associated with 5.19 percent, the fourth quartile with 7.65 percent higher wages.

C Appendix C: Data on the cotton weaving mill

Machine panel. We have 375 months between May 1991 and August 1997 but several machine-month observations drop out from the sample. The Rüti G looms started to operate only in 1992. The old Rüti V machines were out of service in a total of ten months and so did the Toyota looms for three months. So we arrive at a starting sample of 354 machine-months. Errors in the plant's logbooks explain a further loss of thirteen observations: the reported ratio of actual to potential output exceeded one-hundred percent in nine consecutive months with the STB machines, two months with the Rüti V looms, and one month with the Rüti G machines. After dropping the respective observations, the estimation sample covers 341 machine-months. The data were provided by the operating management of the weaving plant in 1998.

Worker panel. Annual payroll data, which cover all weavers (1612 women) employed in the plant at least once between 1988 and 1995. The variables include the date of birth, dates of entry and exit, annual earnings, the type of machine the worker was assigned to (for the longest

Table 14: Alternative ways of capturing import exposure

	(1) Weighted	(2) No large occupations	(3) $1/N_{fot}$	(4) Intensive margin
Importer occupation	0.059***	0.049***		
at importer firm (dummy)	(0.007)	(0.008)		
Importer occupation			0.057***	
at importer firm $\times 1/n_{fot}$			(0.012)	
Importer firm	0.007	0.004	0.020**	
(dummy)	(0.009)	(0.009)	(0.009)	
Specific import per worker				0.014
(1st quartile)				(0.012)
Specific import per worker				0.026**
(2nd quartile)				(0.012)
Specific import per worker				0.051***
(3rd quartile)				(0.013)
Specific import per worker				0.074***
(4th quartile)				(0.014)
Foreign firm	0.190***	0.187***	0.165***	0.136***
(dummy)	(0.010)	(0.011)	(0.013)	(0.013)
Book value of machinery	0.063***	0.064***	0.068***	0.060***
(log)	(0.003)	(0.003)	(0.005)	(0.004)
R^2	0.391	0.442	0.478	0.483
Number of observations	189,913	157,645	189,913	189,913

Notes: The dependent variable is the log monthly earning of the worker in the given year. All specifications control for occupation and year fixed effects, indicators for gender and schooling and a quadratic function of worker age, quadratic functions of log firm employment and firm age. In column 1, observations are weighted by $1/n_{fot}$, the inverse of the number of workes in a firm-occupation-year cell. In column 4, we also control for, but do not report, quartiles of total (as opposed to occupation-specific) import per worker. Standard errors, clustered by firm, are reported in parantheses. Coefficients significantly different from zero at 1, 5 and 10 percent are marked by ***, ** and *, respectively.

period within the year), citizenship and work schedule (workdays versus weekend). The firm's Personnel Department provided the data in 1998.

Worker-machine panel. Identical with the machine panel except for coverage (1991-95) and the inclusion of the mean residual wage of continuing weavers who were assigned to the given type of machine in the given year. The past residual wages were estimated using data from 1989, when a linear payment by results scheme was in effect). The time window is limited by having worker data for 1990-95 and machine data for 1991-97. The estimation sample consists of 261 machine-months with a non-zero output.

D Appendix D: 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 58 FEOR codes involving the operation of a machine (excluding vehicle drivers). Table 15 provides the full list of occupations used.

Table 15: Machine operator occupations

FEOR code	Description
8131	Petroleum refinery and processing machine operators
8133	Basic chemicals and chemical products machine operators
8149	Building materials industry machine operators not elsewhere classified
8199	Processing machine operators, production line workers not elsewhere classified
8219	Mining-plant operators not elsewhere classified
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 not elsewhere classified
8231	Water works machine operators
8232	Sewage plant operators
8240	Packaging machine operators
8293	Agricultural machine operators, mechanics
8299	Other non manufacturing machine operators not elsewhere classified
8311	Agricultural engine drivers and operators
8319	Agricultural and forestry mobile-plant drivers, operators not elsewhere classified
8321	Earth moving equipment operators
8329	Construction machine operators not elsewhere classified
8331	Scavengery machine operators and drivers
8341	Crane operators
8349	Material conveying machine operators not elsewhere classified
8352	Tram drivers
8354	Trolley bus drivers
8355	Car drivers
8359	Vehicle drivers not elsewhere classified
8361	Bargemen
8369	Ships' deck crews and related workers not elsewhere classified

There are 294 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.

First, we tag both occupations and products with simple tags relating to the broad industry in which they might operate. We use 34 tags (Table 16). Each occupation or product can receive multiple tags. Among the occupation–machine matches that have at least one tag in common, we use 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 368 matches.

Table 16: 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

The average worker is matched with 6.34 machines, and the average machine is matched with 1.25 occupations. The full list of matches is available at
https://github.com/korenmiklos/machines-replication/blob/master/table/matches.csv.