Machines and Machinists: Incremental technical change and wage inequality[*]

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February 2020

Abstract

How does incremental improvement in the quality of capital contribute to widening wage inequality? We study the wage effects of imported machinery in Hungary between 1988 and 2004 through the lens of a model. In our model, imported machines are faster and more reliable than old ones. Both characteristics complement worker skill: (i) better workers will be assigned to imported machines, where (ii) their productivity and wage will increase and (iii) their wages will become more unequal. We confirm these predictions in the data. Our estimates imply that about half of the increase in wage inequality among machine operators can be attributed to the increased availability of imported machines. The policy implications of our mechanism are different from the conventional view that certain skills will become obsolete with new technologies.

JEL codes: J31, J24

A prominent view about the steady increase in wage inequality is that new technologies have made certain skills and occupations obsolete. Each new technology complements some skills and substitutes others, leading to differential wage responses across workers. This view is motivated by the fact that wage differences between broad groups of workers (college graduates and high school graduates, production and non-production workers, those doing abstract and routine tasks) have widened significantly during major leaps of technology such as electrification, mass production, computerization and robotization.[1]

[*]We thank Lex Borghans, Rob Johnson, Francis Kramarz, Dalia Marin, Adam Szeidl, Álmos Telegdy, Eric Verhoogen, Andrea Weber and seminar audiences for comments. Péter Harasztosi, Dávid Nagy, Krisztina Orbán, Péter Tóth and Péter Zsohár provided excellent research assistance. This research was funded by the European Commission under its Seventh Framework Programme for Research (Collaborative Project Contract number 217436) and the European Research Council (ERC Starting Grant agreement number 313164). We thank the Databank of the Institute of Economics (mtakti.hu) for providing access to the data.

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[1]See inequality trends reported for the U.S. (Katz, Loveman & Blanchflower 1995, Autor, Katz & Kearney 2008), the U.K. and Japan (Katz et al. 1995), Germany (Dustmann, Ludsteck & Schönberg 2009), Poland (Rutkowski 1996, Rutkowski 1997), the Czech Republic, Hungary, Romania and Slovenia (Rutkowski 1997).

While this view has been successful in explaining wage premia during technological revolutions, it faces two limitations in painting a complete picture about the evolution of wage inequality. First, only part of the inequality can be explained by wage premia between well identified groups. Similar workers have also had diverging wage trends.[2] Second, sweeping technical change is relevant to only some countries in some time periods. For most countries and most time periods, gradual improvement in the quality of otherwise similar capital goods is the dominant form of technical change.[3]

We study how incremental quality improvements of industrial machinery contribute to widening wage inequality. We compare, both theoretically and empirically, similar workers working on similar machines. Our theory suggests a fundamental complementarity between worker skill and machine quality. Even without major task, skill or occupation differences, workers who are somewhat better at their job will be relatively more productive on machines that are somewhat better. This mechanism leads to an increase in wage inequality as machine quality gradually improves. We then confirm the predictions of this model in data on Hungarian machine operators, 1988–2004. Our estimates imply that about half of the increase in wage inequality among machine operators can be attributed to access to better imported machines.

We uncover a novel mechanism of how technical change complements worker skill. This

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Studied technological leaps include steam engines (Katz & Margo 2014, Franck & Galor 2015), electrification (Goldin & Katz 2008, Chapter 3), mass production and its dissolution (Piore & Sabel 1984), automation (Autor, Levy & Murnane 2003, Autor 2015, Acemoglu & Restrepo 2017) and industrial robots (Acemoglu & Restrepo 2019, Dixon, Hong & Wu 2019, Koch, Manuylov & Smolka 2019, Graetz & Michaels 2018, Findeisen, Dauth, Suedekum & Woessner 2018).

[2]Much of the inequality increase has happened within skill and experience groups (Katz & Autor 1999, Acemoglu 2002*b*, Autor et al. 2008). Even within the same occupation, inequality has increased to at least the same extent as across occupations (Kim & Sakamoto 2008). And comparing the wage changes of workers at different percentiles of the wage distribution, one finds pervasive increases in inequality, with higher earners enjoying faster wage growth at all parts of the distribution (Autor, Katz & Kearney 2006, Lemieux 2008, Autor et al. 2008, Dustmann et al. 2009).

[3]Improved quality of industrial machinery, such as increased speed and reliability, has historically served as a major source of labor 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 (Bessen 2012, Table 3). More recently, the quality of durable equipment has almost tripled in the United States between 1947 and 1983 (Gordon 1990, Chapter 3). And these quality improvements are even more relevant to developing and emerging economies where the vast majority of investment is still unrelated to information and communication technologies. 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.

mechanism challenges conventional policy suggestions on how to best protect workers from the negative effects of new technology. Under the prevailing view, the primary task is to identify occupations most at risk of being replaced by technology (Frey & Osborne 2017). This is harder to do when technical change is mostly incremental, because winners and losers may stand next to one another on the shop floor, performing similar tasks. And even after identifying potential losers, helping them switch occupations is hard.[4] Instead, we suggest that good vocational training can endow workers with proper basic skills, which makes adaptation to incrementally new technologies easier.

We now turn to explaining our results in more detail. Machines in our model run autonomously until a problem arises and the operator has to intervene.[5] Better machines are faster and more reliable. Better operators solve problems faster. Faster machines are clearly complementary with worker skill. The opportunity cost of each unit of time while the machine is idle is higher, and better workers can fix machines faster. Perhaps more surprisingly, more reliable machines also require more skilled operators. Because they break down less often, a skilled operator can operate a larger number of reliable machines, making her time and attention more valuable. In our model, this quantity margin dominates and machine reliability and worker skill become complementary. As a result, better machines are assigned to better workers.[6] In addition, because better machines have higher productivity, workers using such machines earn higher wages. And because they are skill augmenting, the wage distribution on new machines is more unequal.

We evaluate the model in data on Hungarian industrial firms between 1988 and 2004. Hungary provides an ideal setting for this analysis. The sudden fall of communism resulted in rapid trade liberalization, especially with respect to technologically advanced countries. This

[4] In German data, workers switching occupations are found to move to an occupation with very similar skill requirements (Gathmann & Schönberg 2010). And among Belgian job seekers, relevant vacancies have at least 80 percent overlap with the unemployed worker's past task experience (Goos, Rademakers, Salomons & Willekens 2019).

[5] This formulation is motivated by our detailed case study of a textile weaving mill, where operators have to intervene from time to time to change the warp and weft, fix broken yarn threads, or solve minor mechanical problems with the machine. We believe the mechanism captures the operation of a large set of machines. In fact, the quality-skill complementarity we discuss below is even stronger for non-autonomous machines.

[6] Eeckhout & Kircher (2018) present general conditions for positive assortative matching when production depends on both the quantity and the quality of two types of inputs. Our complementarity result is a special case of theirs. This quantity effect is 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).

led to arguably exogenous changes in the level of machine quality available to producers. As we document below, imported machines were better than older Hungarian or Soviet machines.[7]

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. The wage dispersion also increases among operators of new machines.

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 with what was then called the European Economic Community 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 imported machinery earn 5 percent more than similar workers at similar firms. We also find that firm-occupation groups with many high-wage workers are the first to start importing. While this selection on wages is consistent with the model prediction that better 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 both the returns to education and the wage dispersion increased with imported machines.[8]

To quantify the effect of exposure to new imported machines on wage inequality, we conduct

[7] Machine quality differs across other countries, too. 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. Historically, Clark (1987) documents large heterogeneity in textile loom productivity across countries.

[8] The estimated wage effects of new, imported machines are similar in our case study and in our broader sample. They are somewhat lower than 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 education are higher on new machines.

the following counterfactual. We measure how wage inequality increased within the group of workers who were not exposed to imported machines. Under the assumptions of the model, this increase in inequality would have characterized the entire sample of machine operators had imports not become available. Between 1992 and 2000, the wage gap between the 90th and the 10th percentile of the distribution has increased by 14.69 percent in the whole sample, but only by 6.93 percent in the non-importer sample. Hence, about half of the increase in inequality can be attributed to the increased availability of imported machines.

Our work is related to the literature on capital-skill complementarity (Griliches 1969, Hamermesh 1993), which finds that the *quantity* of physical capital is complementary to skilled workers. Krusell, Ohanian, Ríos-Rull & Violante (2000) measure the quantity of capital using quality-adjusted price indexes from Gordon (1990). They hence study the joint effect of capital quantity and quality, finding that capital-skill complementarity, defined this way, can explain most of the variation in the skill premium in postwar U.S. data. And Burstein, Cravino & Vogel (2013) and Parro (2013) argue using calibrated general-equilibrium models that imported machinery is skill biased. Our contribution relative to this literature is to show that the *quality* of capital is skill augmenting, while holding capital quantity fixed. We do so in firm- and worker-level micro data. And we also propose a theoretical mechanism for why better machines complement better workers.

A growing literature studies the link between international trade and wage inequality. Most previous studies 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.[9] Importing is also associated with higher wages, and several studies found that importing machinery or intermediates raises the demand for skill.[10] 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 characteristics. Her study had no data on imported machinery.

[9]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.

[10]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.

In contrast to this literature, 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] Closer to our focus, Lindner, Muraközy & Reizer (2018) study low-novelty innovation activities such as process innovation and conclude that they are skill biased.

Section 1 introduces our model. We build an engineering production function in the spirit of Arrow, Levhari & Sheshinski (1972) and Bessen (2012) to study the assignment of machines to workers, machine productivity and worker wages. Because firms engage in rent sharing (Card, Cardoso, Heining & Kline 2018), any effects on 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 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-

[11]Intensive on-the-job training could be an alternative. Spitz-Oener (2006) documents that a large fraction of the increased demand to skill in Germany is due to within-occupation skill upgrading. In Hungary, where the participation of low-educated workers in formal and informal skill-enhancing activities is notoriously low (Köllő 2017), this seems a less plausible explanation.

[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.

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 over time.

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 different ways to find the causal effect of imported machines on wages.

The Appendices contain derivation of our main theoretical result (Appendix A), a robustness analysis of measurement errors in our data (Appendix B), and detailed data descriptions about the weaving mill (Appendix C) and the larger sample (Appendix D).

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.[13]

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.

Let $\pi_1(t)$ denote the probability that the machine is running at time t and $\pi_0(t) = 1 - \pi_1(t)$

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

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.[14] What is the optimal assignment of workers to machines?

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 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 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

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

[14]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.

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).[15]

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

[15] 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.

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.

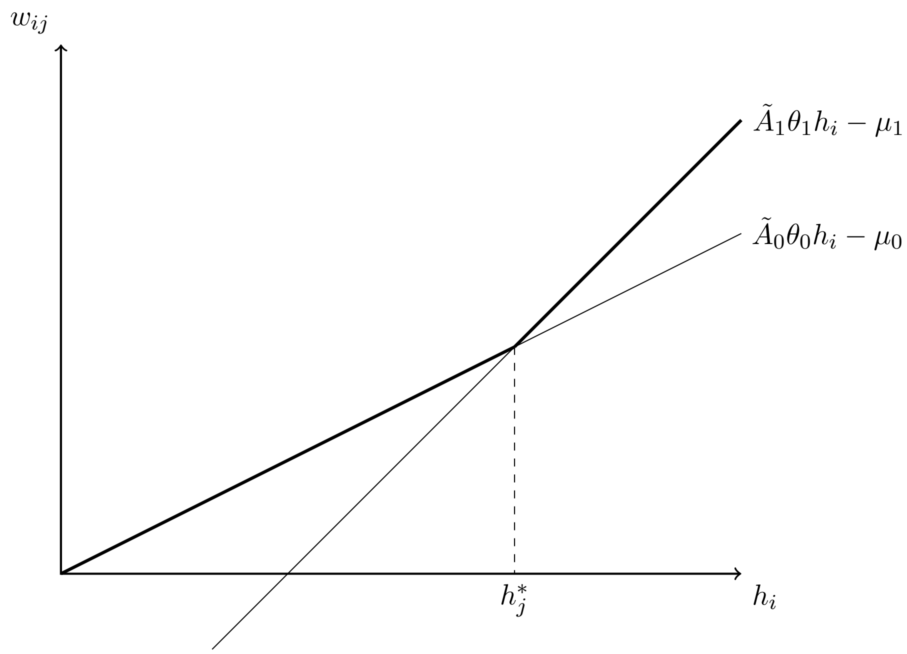


Figure 1: Machine assignment and wage setting by worker skill

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.

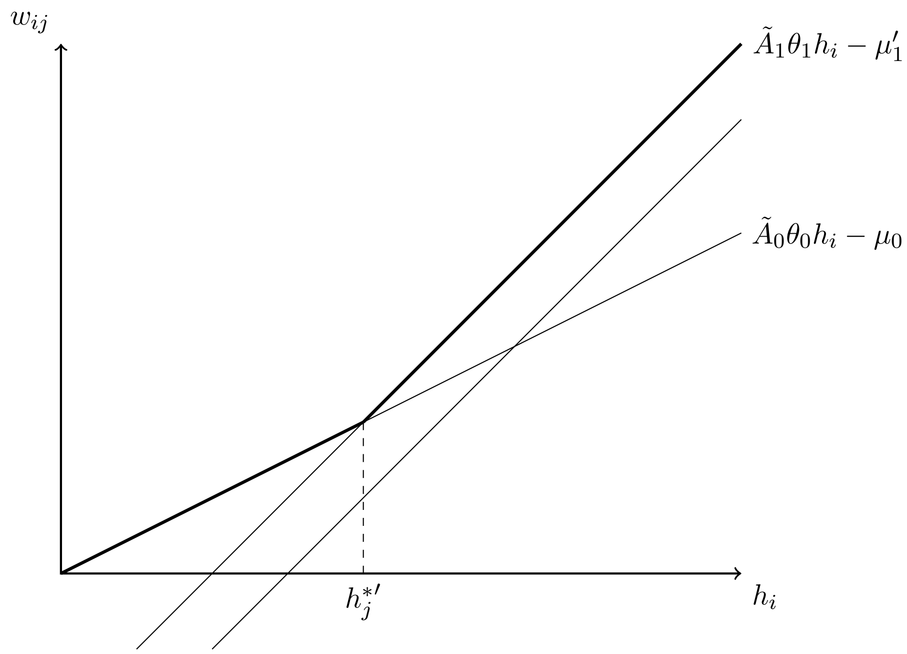


Figure 2: Technology upgrading by worker skill

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 comes from a Hungarian cotton weaving mill, which operated Soviet and Czechoslovakian (STB and UTAS) weaving machines, together with a few older 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).

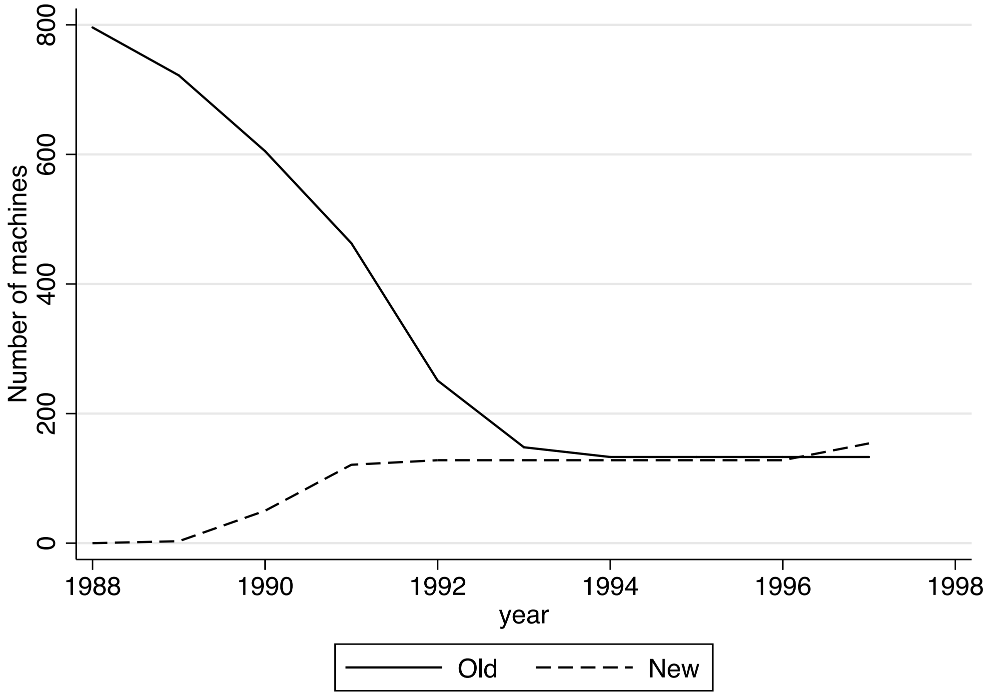


Figure 3: The number of old and new machines, 1988–1997

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 our wish to focus on the period after the plant's initial size reduction, on the other.[16]

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

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

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 ratio of actual to potential output (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.

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

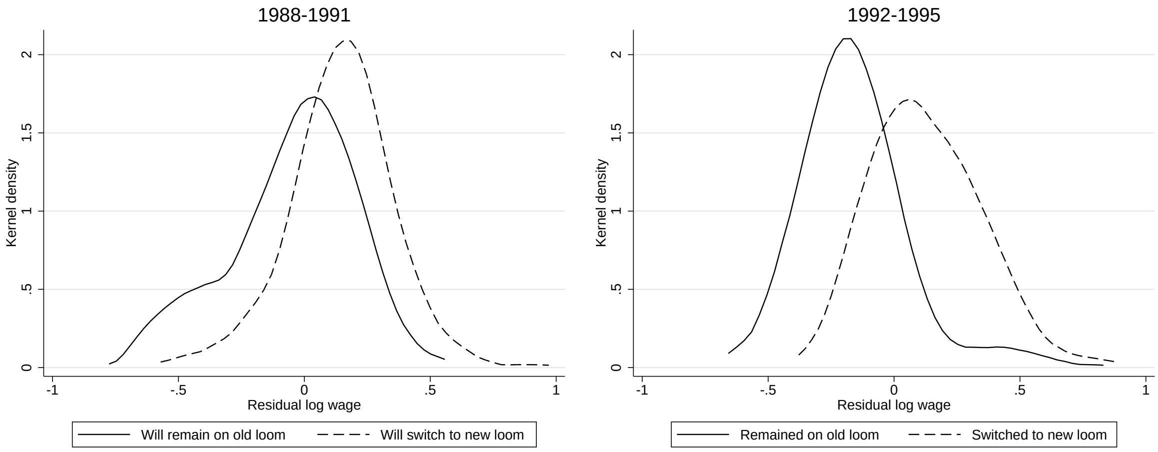
Dependent variable	Mean difference	Mean dep. var.	St. dev. dep. var.
Output (log)	0.820***	5.49	0.475
Potential output (log)	0.790***	5.94	0.449
Potential output/worker (log)	0.811***	3.52	0.845
Output/potential output (log)	0.031*	4.15	0.150
Percent downtime due to			
—scheduled maintenance	−3.20***	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.

Assigning workers to machines. To study which workers will be assigned to new looms, we explore the wage distribution of workers.

Figure 4 plots the kernel density of log wages (relative to the annual mean) in two periods for two groups of workers. The left panel includes the years 1988 to 1991, before new looms were widespread in the firm (see Figure 3) and only workers who are not yet assigned a new loom. The right panel includes the years 1992 to 1995, by which time many new looms were installed and old ones retired.

The solid line represents workers who do not get a new loom in the sample period. The dashed line represents workers who did get one in the second half of the sample. The estimated wage densities in the left panel illustrate *sorting* on (potentially unobservable) skills: workers who will be assigned to new looms have already already higher wages before these looms arrive. The right panel shows the *effect* of importing on the wage distribution. The wage gap between users of new and old looms is even higher that what can be explained by sorting. Moreover, the wage distribution of new loom operators is noticeably more dispersed on the new looms than on the old ones, implying that the new looms increase earnings *inequality*.



Estimated kernel density of residual log wages relative to year mean. Bandwidth = 0.1. Left panel includes workers between 1988 and 1991 who do not yet work on a new loom (406 worker-years). Right panel includes workers between 1992 and 1995 (403 worker-years). Sample is limited to workers who appear in both time periods at least once.

Figure 4: Wage distribution before and after the adoption of new looms

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 2 suggest that a shift from an old to a new machine is associated with a 6 percent wage increase within individual workers' careers. (The ordinary least squares results are presented for comparison.)

Table 2: 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.

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 3). 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 patterns are consistent with the model predictions outlined in Propositions 2 and 3.

Table 3: 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.

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

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 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.[17] 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 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

[17] 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.

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 assume that the effect of imported machines does not vanish over time.[18]

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 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 4 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

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

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.

Table 4: The estimation sample over time

Year	Workers	Firms	Fraction importing (percent)	Import exposure (percent)
1992	11,766	2,129	33.63	16.57
1993	15,226	2,917	38.18	22.73
1994	15,447	3,081	37.65	27.25
1995	16,761	3,206	43.05	30.88
1996	16,302	3,036	48.24	34.35
1997	14,146	2,881	51.86	37.25
1998	15,712	2,929	54.24	40.04
1999	14,782	2,985	56.51	41.65
2000	15,144	3,106	55.26	43.44
2001	14,862	2,976	57.28	45.14
2002	16,199	2,351	52.98	45.99
2003	15,427	2,227	51.44	46.66
2004	15,269	2,258	49.64	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.

We next study how import behavior is correlated with tariffs. Tariffs on imported machinery have significantly declined in the 1990s. (See Table 5.) 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.[19] 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

[19]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 5: 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.

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

Figure 5 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.

4.2 Wages and inequality

Table 6 reports the wage gap between various groups of workers over time. The second column shows the wage difference (in log points) associated with a high-school degree (relative to primary school and vocational school), controlling for worker gender, age and occupation.

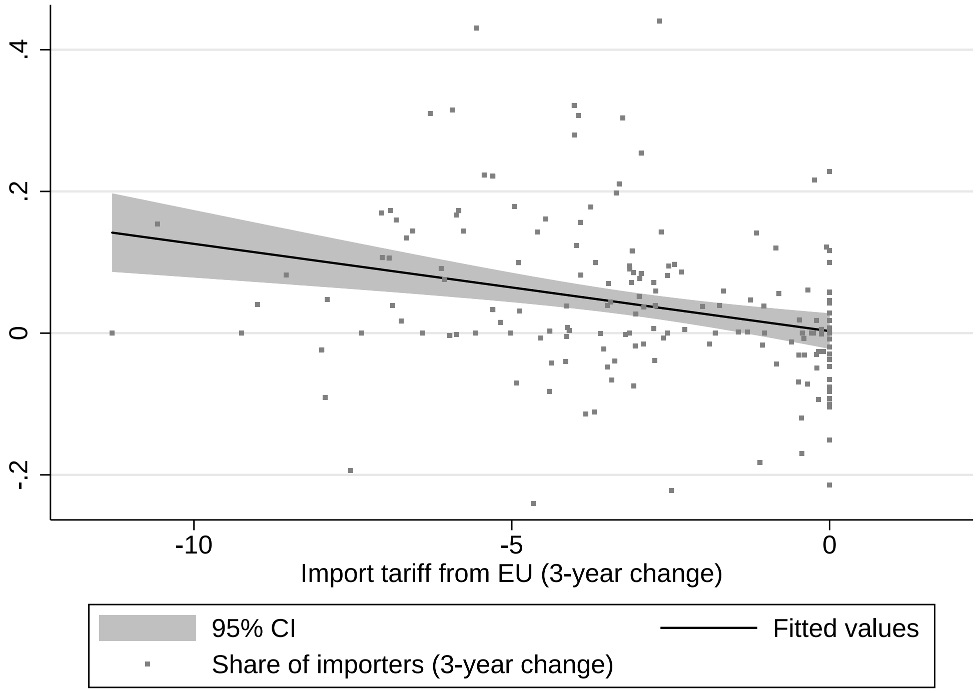


Figure 5: Occupations with faster tariff cuts adopt imported machines faster

The third column shows the log point 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 0.17 log points to 0.20 log points. From 1992 to 2000, the wage gap between the 90th and the 10th percentile of the within-occupation wage distribution has widened from 0.980 to 1.18 log points. 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.

Figure 6 plots the average log wage change between the early and late periods by percentiles of the wage distribution. The solid line represents the actual wage change. In this period, real wages of machine operators have declined, but they declined less for workers at the high end of the distribution. The wage change of workers at the 10th percentile of the distribution was -0.150 log points, whereas those at the 90th percentile had only a -0.013 change. That is, the wage gap between the 10th and 90th percentile has widened by 0.137 log points. The fact that the solid line is continuously increasing throughout the distribution shows a *pervasive* increase

Table 6: Wage inequality over time

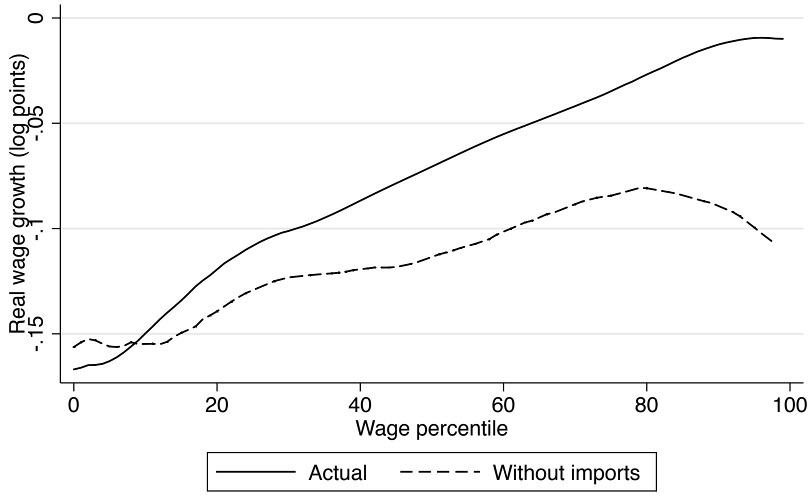
Year	High-school premium	90/10 inequality
1992	0.169	0.980
1993	0.163	1.02
1994	0.183	1.01
1995	0.172	1.01
1996	0.176	1.06
1997	0.188	1.14
1998	0.190	1.15
1999	0.206	1.15
2000	0.196	1.18
2001	0.165	1.08
2002	0.190	0.956
2003	0.139	1.00
2004	0.176	1.03

Notes: Table displays the wage gap between various groups of workers over time. The second column shows the wage difference (in log points) associated with a high-school degree (relative to primary school and vocational school), controlling worker gender, age and occupation. The third column shows the log point 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.

inequality: the wage gap between any two workers has widened in this period.

The dashed line shows counterfactual wage growth, had firms and occupations not been exposed to imported machines. It is constructed as follows. We take firm-occupation cells that did not import any time by 2000 and follow their wage distribution over time. That is, we measure the wage growth at each percentile of the *non-importer* wage distribution.[20] This is a good measure of counterfactual wage growth under the assumptions (maintained in our model) that (i) the skill distribution of workers is constant, and (ii) the returns to skill on non-imported

[20]We also correct for the fact that, because of selection, the within-group wage percentile of a non-importer is not the same as her overall wage percentile. In practice, however, this correction is small. For example, the worker at the 10th percentile of the overall distribution is at the 11.6th percentile of the non-importer distribution.



Notes: Nonparametric estimates of log wage change between two periods by percentile of the wage distribution. Early period is 1992-1994 (15,205 worker-years), late period is 1998-2000 (17,475 worker-years). Firm-occupation cells that have already imported by 1994 are excluded. Counterfactua growth computed from firm-occupations cells that never import. Lowess curve with bandwidth of 0.33.

Figure 6: Actual and counterfactual wage change by wage percentile

machines are not affected by importing.

Without imports, real wages would have declined even more. The wage gap between high- and low-wage workers would, in turn, not have widened as much as it actually did. Real wage change at the 10th percentile would have been practically the same as in the data, -0.155 log points. At the 90th percentile, wage change would have been -0.088. The 90/10 wage gap would have hence only widened by 0.067 log points. Comparing the dashed line to the solid line, we can conclude that, even at other parts of the distribution, inequality would have increased without importing about half as much as it actually did. Hence about half of the increase in inequality between 1992 and 2000 can be attributed to importing.[21]

[21] Although consistent with our model, the estimated effect of importing on inequality can be biased in both directions in a richer model. First, importing workers may differ not only in their initial wage (because of selection on time invariant skill), but also their counterfactual wage growth may be higher than observed wage growth of non-importers at the same initial wage level. In this case, we would *overestimate* the contribution of importing to inequality growth. We address this omitted variable bias empirically below. Second, we have assumed that wages of non-importers are not affected by the presence of imported machines. In general equilibrium, however, high-skilled workers' wages may increase in response to imported machines. Even if they do not use these directly, the presence of many imported machines in the economy can increase the outside option of high-skilled workers, their bargaining power, and, hence, their wages. This mechanism leads to an *underestimation* of the relative contribution of importing to inequality growth.

4.3 When do firms import?

Table 4 showed that, over time, more and more workers are exposed to imports. 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:

$$\Pr(M_{jt} = 1 | M_{j,t-1} = 0) = \nu_t + \alpha X_{jt}. \tag{10}$$

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.

The first column of Table 7 report the result of a firm-year hazard regression. We find that firms with more capital, more labor and foreign firms are more likely to start importing in any given year. Columns 2 and 3 report regressions at the firm-occupation-year level. Column 2 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 3, 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.[22] 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

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

Table 7: When do firms start importing?

	(1) Hazard of importing	(2) Occupation level	(3) Tariff interactions
Book value of machinery	0.052***	0.009***	0.005***
(log)	(0.006)	(0.000)	(0.000)
Employment	0.057***	-0.002***	-0.003***
(log)	(0.010)	(0.001)	(0.001)
Foreign firm	0.312***	0.056***	0.030***
(dummy)	(0.019)	(0.003)	(0.002)
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	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.

function ν_{ot} and on tariffs τ_{ot}^{EU}, interacted with firm size and foreign ownership:

$$\begin{aligned}\Pr(\chi_{jot} = 1 | \chi_{jo,t-1} = 0) = \nu_{ot} + \alpha X_{jt} \\ + \tau_{ot}^{\mathrm{EU}}[\gamma_0 + \gamma_1(1 - F_{jt}) \ln K_{jt} + \gamma_2(1 - F_{jt}) \ln L_{jt} \\ + \gamma_3 F_{jt} + \gamma_4 F_{jt} \ln K_{jt} + \gamma_5 F_{jt} \ln L_{jt}]. \quad (11)\end{aligned}$$

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 captured 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 3 of Table 7 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.

To proxy for skill, we use the ranking of the workers in the within-occupation wage distribution. 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 7 displays the frequency of these three categories for each wage quintile. Consistently with the model, early importers are overrepresented among high-wage workers. Late importers have a balanced distribution of wages, whereas workers that never import tend to have a lower wage.

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)

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

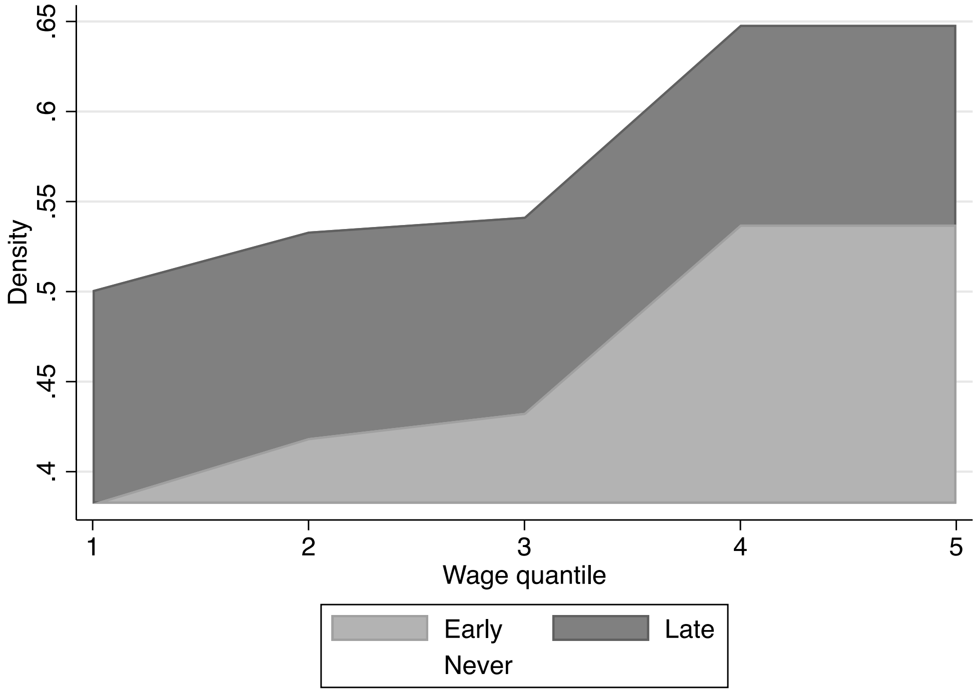


Figure 7: Among high-wage workers, early importers are overrepresented

We map this to the available data as follows.

$$\ln w_{ijot} = \nu_{ot} + \nu_{jt} + \gamma_h h_i + \gamma_\chi \chi_{jot} + \gamma_{\chi h} \chi_{jot} h_i + u_{ijot}. \tag{12}$$

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 8 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.[23]

We discuss instrumental variables estimates below.

Table 9 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

[23]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 8: 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.

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.

Table 9: 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.

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 (11).

Taking the predicted value from equation (11) as

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

we have an estimated hazard of importing. We then calculate the predicted probability of a 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 10: 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.

Table 10 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 8 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 of Table 8, we include firm-year fixed effects in both the first and second stages of the 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 9 show, the returns to skill increase in firm-occupations that are induced to import by tariff reductions.

5.3 Robustness

Table 11 reports the results of wage regressions with various number of firm controls. Column 1 reports 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 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.

Table 11: 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.

Appendix B contains further robustness checks.

6 Conclusions

We showed in Hungarian linked employer-employee data for 1988–2004 that machine operators exposed to imported machines earn higher wages than similar workers at similar firms. Using product-specific tariff rates as instruments for importing suggests that the importer wage premium is causal. Wage inequality increased in our sample, more so in occupations exposed to imported machines. We built a model to explain which workers use imported machines and how this affects wages. Our estimates suggest that about half of the increase in inequality can be attributed to imported machines.

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. The cross-firm variation in vintages could help explain the cross-firm inequality in wages (Hornstein, Krusell & Violante 2002). Third, the better quality of imported machines could be endogenized in a model of directed technical change (Acemoglu 1998, Acemoglu 2002*a*) 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,

$$L(h) = \bar{L}(h)\,[w(h) - b]^{\gamma} \text{ for all } h. \tag{13}$$

The demand for total operator time is equal to,

$$\sum_m k_m(h) \frac{1}{1+\theta_m h} = \bar{L}(h)\,[w(h) - b]^{\gamma} \text{ for all } h. \tag{14}$$

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 (14) and μ_m is the Lagrange multiplier of (4).

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

$$-\sum_m k_m(h)\frac{1}{1+\theta_m h} + \lambda(h)\gamma\bar{L}(h)[w(h)-b]^{\gamma-1} = 0. \tag{15}$$

Substituting into (14),

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

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

$$w(h) = \frac{\gamma}{1+\gamma}b + \frac{1}{1+\gamma}\left[(A_m - \mu_m)\theta_m h - \mu_m\right]. \tag{16}$$

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

$$w_{ijot} = \xi\chi_{ijot} + \varepsilon_{ijot}, \tag{17}$$

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 (17) by simply regressing wages on the importer dummy and would get a consistent estimate of ξ.[24]

However, we only observe

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

and estimate

$$w_{ijot} = b\chi_{jot} + \varepsilon_{ijot}. \tag{18}$$

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

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

$$\operatorname{plim} \hat{b}_{OLS} = \mathrm{E}\left(w_{ijot} | \chi_{jot} = 1\right) - \mathrm{E}\left(w_{ijot} | \chi_{jot} = 0\right) = \xi \Pr(\chi_{ijot} = 1 | \chi_{jot} = 1) < \xi. \tag{19}$$

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

When we include firm fixed effects in (18), the estimate of b becomes

$$\hat{b}_{FE} = \frac{\sum_{jt} (\bar{w}_{1ft} - \bar{w}_{0ft}) n_{0ft} n_{1ft} / n_{jt}}{\sum_{jt} n_{0ft} n_{1ft} / n_{jt}}, \tag{20}$$

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.

$$\operatorname{plim} \hat{b}_{FE} = \xi \frac{\sum_{jt} \Pr(\chi_{ijot} = 1 | \chi_{jot} = 1) n_{0ft} n_{1ft} / n_{jt}}{\sum_{jt} n_{0ft} n_{1ft} / n_{jt}} < \xi. \tag{21}$$

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 12 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 8.

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 12. 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 12 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

$$w_{ijot} = \sum_{m=1}^{4} \xi^{(m)} S_{jot}^{(m)} + +\alpha X_{jt} + u_{ijot}. \tag{22}$$

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 12 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

Table 12: 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.

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 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 13 provides the full list of occupations used.

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 14). 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.

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

Table 13: 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

https://github.com/korenmiklos/machines-replication/blob/master/table/matches.csv.

Table 14: 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