Machines and Machinists: Importing Skill-Biased Technology*

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Abstract

We build a model of technology choice with heterogeneous firms and workers to study how imported technology affects wages. Imported machines increase the productivity of worker-firm matches, but are more expensive than domestic ones. More productive firms and more skilled workers are hence more likely to use an imported machine. We study trade liberalization in the model, which makes imported machines cheaper. Both the direct and the equilibrium implications of trade liberalization increase the returns to skill. We use linked employer-employee data on Hungarian machine operators for 1992-2003 to test the predictions of the model. Machine operators exposed to imported machines earn higher wages than similar workers at similar firms. The returns to skill have increased in our sample between 1992 and 2000. A quarter of the increase can be attributed to greater exposure to imported machines. Our results suggest that imported machines can help propagate skill-biased technical change.

Why has wage inequality increased in the past decades? The two main explanations are increased openness of international good markets (globalization) and skill-biased technical change (SBTC). The first states that increased trade competition with low-wage countries reduces the demand for unskilled labor.[1] The second argues that computerization and automation has reduced the demand for various routine skills.[2] In both explanations, the wages of skilled workers increase relative to unskilled workers.

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[1]See Robert C Feenstra & Gordon H Hanson (2003) for an overview; G J Borjas, R B Freeman & L F Katz (1997) for earlier and David H Autor, David Dorn, Gordon H Hanson & Jae Song (2014) for more recent evidence from the U.S.

[2]See Lawrence F Katz & David H Autor (1999) for an overview; David H Autor, Frank Levy & Richard J Murnane (2003) for U.S. evidence and Maarten Goos, Alan Manning & Anna Salomons (2014) for evidence from 16 European countries.

In this paper, we argue that the two explanations are not exclusive but, rather, complementary. When skill-biased technology is embodied in imported machinery, globalization is a necessary precondition for SBTC to reach lower-income countries. These countries import a large fraction of their machinery (Jonathan Eaton & Samuel Kortum 2001). Once they open up to trade, they become more exposed to the computerization and automation that have affected high-income countries since the 1980s.[3]

We build a model of heterogeneous firms and workers who meet after surmounting search frictions. They then jointly decide whether to use domestic or imported machinery. Imported machinery offers higher returns to worker skill (and firm productivity), but is more expensive. More skilled workers and more productive firms will opt for using imported machinery. We derive how wages depend on firm productivity, worker skill, and the decision to use imported machinery. Importing affects wages through the direct effect of higher productivity (as profits are shared with workers), but also through a change in outside options of workers.

To study how globalization affects the wage distribution, we ask what happens in the model when the price of imported machinery falls. As more and more high-skill workers start using more productive imported machinery, their wages go up. Importantly, because their employment prospects have become better, skilled workers enjoy a wage increase even if they do not currently work on an imported machine. Both effects raise the returns to skill, thus contributing to increased wage inequality.

We use Hungarian linked employer-employee data from 1992-2003 to evaluate the predictions of the model. In this time period, after the fall of communism in 1989 and before joining the European Union in 2004, Hungary witnessed rapid import liberalization. An additional benefit of our application is the richness of the data, which permits us to focus on operators of specialized manufacturing machinery, who are most likely to be directly affected by machinery imports.

We find that machine operators exposed to imported machinery earn 5.63 percent more than similar workers at similar firms. Once we control for a model-consistent measure of worker skill non-parametrically, we find an importer premium of 3.51 percent. As the model predicts, better firms self-select into importing machinery. To account for this fact, we also condition on firm-year fixed effects. We find that importing workers earn 2.14 percent more than nonimporting workers within the same firm. These returns are roughly one third of the returns to having a high school education. The estimated wage returns to being exposed to foreign machines are slightly lower than the returns to computer use, as reported by Alexandra Spitz-Oener (2008) and Benoit Dostie, Rajshri Jayaraman & Mathieu Trépanier (2010).

We address the selection of firms and workers by using European Economic Community (EEC) tariffs as instruments. Given Hungary's small weight rela-

[3]There is accumulating evidence that trade and SBTC are interrelated. Pinelopi K Goldberg & Nina Pavcnik (2007) show that the increases in inequality in seven developing economies have been coincidental with increased trade openness. Ann Harrison & Gordon Hanson (1999) exploit the Mexican trade reform in 1985 to study relative wage and relative employment of white-collar workers. The demand for white-collar workers has increased in plants with higher technology licensing and machinery imports. Ohad Raveh & Ariell Reshef (2016) show that increased imports of technologically advanced machinery is associated with an increased skill premium in a panel of 21 developing countries. We discuss direct micro evidence later.

tive to the EEC, these are likely to be exogenous to firms' technology choice. Interacting these tariffs with firm size, we find that large and medium-sized firms are more likely to start importing when tariffs fall. When we use the predicted import probability as an instrument for actual importing, we find large and significant importer wage premia.

Turning to the effects of trade liberalization, we show that the increased availability of imported machines between 1992 and 2000 has increased the returns to skill by 2.64 percent.[4] This is about a quarter of the 9.68 percent increase in the returns to skill that happened during this same period. We also find that the returns to skill increased slightly among non-importers. This is consistent with the model, where skilled non-importers have a better chance of finding a high paying importer job and can bargain for higher wages.

We also see that, consistently with the model, high-skill workers are the first to obtain imported machines. This is another piece of evidence that imported technology is skill biased, and contributes to a faster rise in the skill premium.

The search frictions assumed in our model ensure that neither firm nor worker characteristics are sufficient to fully describe import behavior and wages. Some firms get lucky and meet a skilled worker, and will hence import and pay a high wage. Similarly, some workers get lucky and meet a productive firm, earning a higher wage than similar workers. The dispersion of wages across otherwise similar workers and firms is an important feature of the data (Erling Barth, Alex Bryson, James C Davis & Richard Freeman 2014, David Card, Jörg Heining & Patrick Kline 2013, Anders Akerman, Elhanan Helpman, Oleg Itskhoki, Marc-Andreas Muendler & Stephen Redding 2013). We follow Fabien Postel-Vinay & Jean-Marc Robin (2002) in assuming that search frictions are large enough so that the matching of firms and workers is random. This is in contrast with models with assortative matching, where more productive firms hire more skilled workers. Many of these models feature a single dimension of hetereogeneity and are hence incapable of explaining the firm- and worker-variaton in wages.[5]

The skill-bias of imported machinery emerges from the supermodularity of the production function in machine quality and worker skill. Our results hence suggest that machines imported by Hungary are more sophisticated and of a higher quality than those produced domestically.[6] Sophisticated machines, in turn, require highly trained, skillful and attentive operators. Operating CNC lathes, for example, requires more training than operating traditional lathes. More broadly, computerization has increased the demand for complex skills (Autor, Levy & Murnane 2003), even within the same occupation (Alexandra Spitz-Oener 2006).[7]

[4]We stop this exercise in 2000 because the minimum wage has been increased drastically the following year, reshaping the wage distribution.

[5]Stephen Ross Yeaple (2005) builds a Roy-type model of technology choice, where labor reallocation is frictionless. Arnaud Costinot & Jonathan Vogel (2010) provide general results about trade and inequality in Roy-type models. Gonzague Vannoorenberghe (2011) and James Harrigan & Ariell Reshef (2015) develop models with heterogeneous firms in the spirit of M J Melitz (2003), in which firms also differ in their demand for skill.

[6]In a different setting, most Indian users find computer numerically controlled (CNC) machine tools imported from Japan and Taiwan to be more reliable, more accurate and more productive than similar Indian machines (John Sutton 2000).

[7]Ethan Lewis (2011) presents evidence of an alternative mechanism on why firms might

For simplicity, we assume that firms can rent domestic and imported machines in frictionless markets (potentially subject to import tariffs). While a similar assumption is often made by a large literature on trade and technology choice (see below), this assumption rules out potentially interesting capital composition effects. When firms can only sell their existing machinery at a discount (Valerie A Ramey & Matthew D Shapiro 2001), they will hold on to machines which are suboptimal matches to their productivity and the skill of their existing workers. This would introduce additional heterogenity across firms, as the decision to upgrade to imported machinery would also depend on the composition of their capital. While we show some evidence for such composition effects in the data, we omit them from the model to focus on the issues of labor market frictions and wage setting.

Our work is related to several strands of literature. First, there is a growing literature studying trade and wages at the firm- and worker-level. This literature started out focusing on the effects of exporting, showing that exporters pay higher wages than non-exporters.[8] Importing is also associated with higher wages, and several studies found that importing machinery or intermediates raises the demand for skill.[9]

Second, the decision to use imported machinery is a form of technology choice, so our paper is naturally related to the literature on trade and technology upgrading. Daron Acemoglu (2003) develops a model of endogenous technology, in which globalization induces the skill-intensive sector to expand and is hence a driver of SBTC. J Costantini & M Melitz (2007) and Andrew Atkeson & Ariel Tomás Burstein (2010) study how globalization interacts with technology upgrading and firm size. Evidence for such trade-induced technology upgrading is provided by E A Verhoogen (2007) and Frias, Kaplan & Verhoogen (2012) for Mexico, by Paula Bustos (2011*b*) and Paula Bustos (2011*a*) for Argentina, and Esther Ann Bøler, Andreas Moxnes & Karen Helene Ulltveit-Moe (2015) for Norway.

Our paper is most closely related to Ariel Burstein, Javier Cravino & Jonathan Vogel (2013) and Fernando Parro (2013), who build multi-country general equilibrium models to show that if imported capital is complementary to skill, globalization can lead to increased inequality. Raveh & Reshef (2016) provide evidence for this mechanism in a panel of 21 countries. Our paper is the first to study the imports of skill-biased technology in micro data.

Relative to the literature, we make three main contributions. First, we focus on imported machinery as the potential driver for the demand for skill. This is

adopt different technology mixes, which is related to the availability of (low-skill) immigrant workers.

[8]See A B Bernard, J B Jensen & R Z Lawrence (1995) for the U.S., Mary Amiti & Donald R Davis (2012) for Indonesia, Irene Brambilla, Daniel Lederman & Guido Porto (2012) for Argentina, Thorsten Schank, Claus Schnabel & Joachim Wagner (2007) for Germany, Judith A Frias, David S Kaplan & Eric Verhoogen (2012) for Mexico, and Pravin Krishna, Jennifer P Poole & Mine Zeynep Senses (2011) for Brazil.

[9]See Harrison & Hanson (1999) for Mexico, Hiroyuki Kasahara, Yawen Liang & Joel Rodrigue (2013) for Indonesia, Garth Frazer (2013) for Rwanda, and David Hummels, Rasmus Jørgensen, Jakob Munch & Chong 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. By contrast, Mary Amiti & Lisa Cameron (2012) found that reducing input tariffs reduces the skill premium within Indonesian plants.

different from the demand effects of globalization, which imply greater export opportunities and more intense import competition. Our proposed mechanism may be more relevant than demand-based explanations for a wide range of countries which import most of their machinery (Eaton & Kortum 2001). It is important to study the imports of specialized manufacturing equipment separately from other channels of globalization, because the composition of trade varies greatly across countries (F Caselli & D J Wilson 2004, Raveh & Reshef 2016).

Second, we study not only average wages of broad classes of workers, but also the within-firm, within-occupation wage distribution. Recent analyses have pointed out that differences in average wages for observationally equivalent workers across firms and across individuals within firms account for a substantial part of the increase in wage inequality.[10] Most previous studies on the link between firms' exposure to international trade have concentrated the mechanisms linking firm-level wage differentials to trade exposure (Elhanan Helpman, Oleg Itskhoki, Marc-Andreas Muendler & Stephen J Redding 2012, Verhoogen 2007, Bustos 2011*a*). By contrast, we focus on within-firm wage inequality, showing how imported technology can lead to increasing wage differences across job-cells and higher inequality within firms (and job cells).[11] The evidence we present supports the notion that both across- and within-firm wage dispersion rises due to the use of imported machinery.[12] This is an important contribution, as we show novel evidence on how trade might lead to a rise in the returns to (unobservable) skills.

Third, we study the indirect effects of trade liberalization with the help of a general-equilibrium model. In the model, as in the data, even non-importer workers gain higher wages after trade liberalization, provided they are skilled enough. This spillover comes about because of an increased demand for skill, and is typically missed by microeconometric studies comparing importing to non-importing firms.

1 A model of techology choice and wage determination

We build a model to explain which workers and which firms use imported machines and how this affects wages. Workers differ in skill, firms differ in productivity. We follow Pierre Cahuc, Fabien Postel-Vinay & Jean-Marc Robin (2006) and Postel-Vinay & Robin (2002), and build a Diamond-Mortensen-Pissarides framework, where workers and firms need to search in order to form a productive

[10] While some studies find that across-firm heterogeneity accounts for the rise in wage inequality in the U.S. (Barth et al. 2014) and Germany (Card, Heining & Kline 2013), for example, Akerman et al. (2013) document that most of the recent increase in Sweden is due to within-firm wage inequality.

[11] Supporting our findings, Frias, Kaplan & Verhoogen (2012) present evidence that exposure to international trade increased within-plant inequality in Mexico.

[12] There is ample evidence that SBTC has also affected the wage distribution within broad occupations. Autor, Levy & Murnane (2003) show how the returns to particular skills have changed in the U.S. Spitz-Oener (2006) shows how particular skills have gained importance within narrow occupations in Germany. We also document that the wage inequality of machine operators in Hungary has increased within narrowly defined occupations. For our application, comparing college and high school graduates, or comparing production to non-production workers would be inappropriate. Machine operators are all production workers and very few of them have college degrees.

match.[13] They then engage in Nash bargaining to split the surplus generated by the match. The wage rate of the worker is the solution to this bargaining.

A worker needs a machine to be productive. Machines are rented in frictionless markets. Because we focus on frictions in the labor market, we decided to simplify the analys of the machine market.[14] There are two types of machines: domestic and imported. Imported machines are more productive but are more expensive to rent. The worker and the firm jointly decide on which machine to use in order to maximize the surplus. Because machine markets are frictionless, the choice of machine is akin to a choice of technology, as analyzed in Costantini & Melitz (2007), Atkeson & Burstein (2010), Verhoogen (2007), Bustos (2011*b*), and Bøler, Moxnes & Ulltveit-Moe (2015). Productive worker-firm matches, which can produce more on a single machine, decide to use an imported machine; others will use a domestic machine.

We solve for the steady state of this model and consider simple comparative statics. We derive the wage equation in the model and show which worker-firm matches use an imported machine. We also consider the comparative static exercise of reducing the rental cost of imported machinery. This can be thought of as trade liberalization.

The theory considers firms with only one worker and only two types of machines. Section 1.6 shows how to parametrize and reinterpret the model to better match the data, in which firms have many workers and can use multiple machines.

1.1 Workers, firms and production

There is a continuum of workers of total measure L. They are characterized by a scalar measure of skill, indexed by $h \in [\underline{h}, \bar{h}]$. The distribution of skill, with cumulative distribution function G_h, is exogenous and is held fixed throughout the analysis. Workers are risk neutral and maximize the present discounted value of wages. They discount the future at rate ρ.

There is a continuum of firms of total measure N. They are characterized by a scalar measure of productivity, indexed by $\omega \in [\underline{\omega}, \bar{\omega}]$. The distribution of productivity, with cumulative distribution function G_ω, is exogenous and is held fixed throughout the analysis. Firms are risk neutral and maximize the present discounted value of profits. They discount the future at rate ρ.

Each worker-firm match needs a machine to produce. There are two types of machines: domestic (D) and foreign (F). A machine of type $i = D, F$ operated by a worker h at a firm ω produces

$$A_i F(\omega, h)$$

output per unit of time, where A_i is the quality of the machine ($A_F > A_D$), and $F()$ is a neoclassical production function, increasing in both arguments and

[13] Related but different models include Elhanan Helpman & Oleg Itskhoki (2010), Gabriel Felbermayr, Julien Prat & Hans-Jörg Schmerer (2011), which do not include worker heterogeneity; Elhanan Helpman, Oleg Itskhoki & Stephen Redding (2010), in which worker skill is unobserved; and Thomas Sampson (2014), where matching is frictionless.

[14] Frictions in buying and selling machines would complicate the analysis of dynamic adjustment: some firms would remain stuck with a suboptimal machine and not adjust because of frictions. The state space would be much wider: firms would differ not only in their productivity and in the skill of their worker, but also in the type of machine they have invested in the past.

homogeneous of degree one. Firms produce a homogeneous product, the price of which we normalize to one.

Machines are rented in frictionless markets, with a type i machine costing R_i per unit of time ($R_F > R_D$). We can microfound the rental rate by assuming that perfectly competitive risk neutral firms, discounting cash flows at rate ρ, buy machine i for price P_i and rent it out at the break-even rate of $R_i = \rho P_i$. As long as $P_F > P_D$, we have $R_F > R_D$.

1.2 The choice to import

Let

$$\phi(\omega, h) \equiv \max_i [A_i F(\omega, h) - R_i]$$

denote the flow production of a worker-firm match net of machine rental costs.

Worker-firm matches jointly decide which machine to use. Because machines can be rented in frictionless markets, they will select, at each point in time, the type of machine that maximizes the net output ϕ.

Let $\chi(\omega, h) \in \{0, 1\}$ denote the import decision of a match, being 1 for an imported machine and 0 for a domestic one. Because $A_F > A_D$ and $R_F > R_D$, only those matches will import that can produce enough to cover the additional rental cost of the imported machine:

$$\chi(\omega, h) = \begin{cases} 1 & \text{if } F(\omega, h) \geq \frac{R_F - R_D}{A_F - A_D} \\ 0 & \text{otherwise.} \end{cases} \tag{1}$$

Let $\theta = (R_F - R_D)/(A_F - A_D)$ denote the minimum production which makes imported machines profitable. Figure 1 shows the choice of machines as a function of firm productivity and worker skill. Clearly, more productive firms and more skilled workers choose imported machines.

The production of a worker-firm match can be written as

$$\phi(\omega, h) = A_D F(\omega, h) - R_D + \chi(\omega, h)(A_F - A_D)[F(\omega, h) - \theta]. \tag{2}$$

1.3 Matching, bargaining and wages

Define the value of workers as the present discounted value of expected future income. The state variable of a worker is her skill h (invariant over time), and the type ω of firm they are matched with. When the worker is unmatched, she is unemployed. The state of the worker follows a Markov chain. An unemployed worker of type h is matched, independently of h, with a random firm with Poisson intensity λ. Matches are dissolved exogenously with Poisson intensity δ, making the worker unemployed. Workers collect unemployment benefit $b(h)$ while unemployed, with $b' \geq 0$,[15] and receive wage $w(\omega, h)$ when matched with a type-ω firm. This wage function is endogenously determined through bargaining, and is the key object of interest.

The value of being unemployed is given by the following Hamilton-Jacobi-Bellman (HJB) equation.

$$\rho V_0(h) = b(h) + \lambda E_\omega [V(\omega, h) - V_0(h)] \tag{3}$$

[15] We can also think of $b(h)$ as the opportunity cost of work, for example, the output of home production.

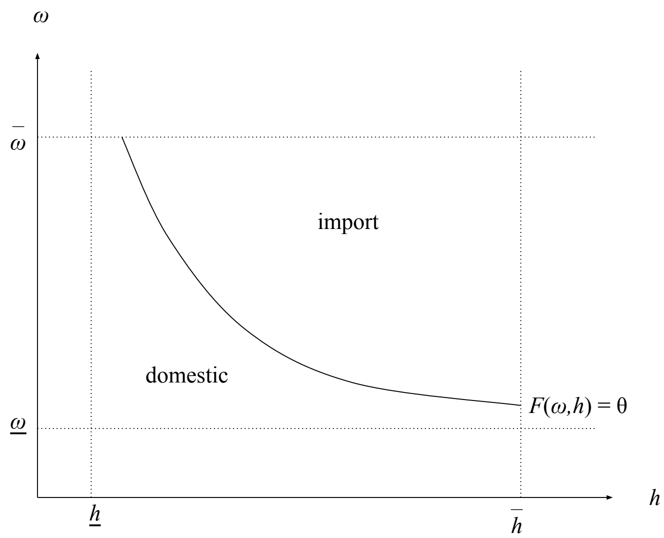

Figure 1: More productive firms and more skilled workers choose imported machines

The annuity value of unemployment equals the flow benefits $b(h)$ plus the expected capital gain. With arrival rate λ the worker finds a random job yielding her the value $V(\omega, h)$. Expectations are taken over the set of acceptable vacancies,

$$E_\omega[V(\omega, h) - V_0(h)] = \int_{\omega: V(\omega,h) > V_0(h)} [V(\omega, h) - V_0(h)] dG_\omega.$$

We will show that, in equilibrium, this is the same as the set of all available vacancies.

The value of being matched to an acceptable firm ω is

$$\rho V(\omega, h) = w(\omega, h) + \delta[V_0(h) - V(\omega, h)]. \tag{4}$$

The worker receives a flow wage and anticipates a capital loss from being fired.

We can write the HJB equations of firms similarly. Firm value is the present discounted value of expected future profits. The state variables of the firm are its productivity ω (invariant over time) and the type h of worker it is matched with. Unmatched firms are maintaining a vacancy at per-period cost c. Matched firms produce net output $\phi(\omega, h)$ and pay out a wage $w(\omega, h)$. The value of a vacant position at firm ω is

$$\rho J_0(\omega) = -c + \eta E_h[J(\omega, h) - J_0(\omega)]. \tag{5}$$

The firm pays c per unit of time to maintain the vacancy. Vacancies are filled at the rate η, at which point the firm earns the expected value. Expectation is taken over the set of acceptable workers,

$$E_h[J(\omega, h) - J_0(\omega)] = \int_{h: J(\omega,h) > J_0(\omega)} [J(\omega, h) - J_0(\omega)] dG_h.$$

Again, in equilibrium, this corresponds to the set of all possible matches.

The value of a filled job for the firm is

$$\rho J(\omega, h) = \phi(\omega, h) - w(\omega, h) + \delta[J_0(\omega) - J(\omega, h)]. \tag{6}$$

The firm keeps the output above the wage paid to the worker and anticipates a capital loss when the match is terminated.

When a worker and a firm meet, they engage in Nash bargaining and split the surplus of the match in constant proportions. The wage function is the outcome of this bargaining. The surplus of a match is

$$S(\omega, h) = V(\omega, h) + J(\omega, h) - V_0(h) - J_0(\omega). \tag{7}$$

The worker gets a β share of this surplus,

$$V(\omega, h) - V_0(h) = \beta S(\omega, h), \tag{8}$$

with the firm getting $1 - \beta$

$$J(\omega, h) - J_0(\omega) = (1 - \beta) S(\omega, h). \tag{9}$$

Combining equations (4), (6), (11), (8) and (9), we can write the wage function as

$$w(\omega, h) = \beta\phi(\omega, h) + (1 - \beta)\rho V_0(h) - \beta\rho J_0(\omega). \tag{10}$$

In each period, the worker gets a β share of output plus a $(1 - \beta)$ share of the flow value of her outside option. She also has to partially compensate the firm for the loss of its outside option.

Combining equations (4), (6), (11), (8) and (9), we can express the surplus of a match as

$$S(\omega, h) = \frac{1}{\rho + \delta}[\phi(\omega, h) - \rho V_0(h) - \rho J_0(\omega)]. \tag{11}$$

1.4 Equilibrium

In this section we define a steady-state equilibrium, in which flows in and out of unemployment are balanced for each type of worker so that the stocks of workers, vacancies, and worker-firm matches are fixed over time. We first introduce a constant-return-to-scale matching function. This matching function translates the stocks of unemployed workers and vacancies into a speed of matching, thereby endogenizing λ and η.

Let $u(h)$ denote the stock of unemployed workers of skill h. Similarly, let $v(\omega)$ denote the stock of vacancies with productivity ω. The total number of matches created in an infinitesimal time period is

$$M(u, v) \equiv M\left[\int_h u(h)dh, \int_\omega v(\omega)d\omega\right].$$

That is, new matches arise with a Poisson arrival rate of M. We have defined the overall stock of unemployed workers as u and the overall stock of vacancies as v. We assume that the function $M()$ homogeneous of degree one in its two arguments. As a result, it is also homogeneous in $\{u(h), v(\omega)\}$.

Once a match arises, it is randomly allocated across searching workers and firms. A new match is of type (ω, h) with probability $v(\omega)u(h)/(uv)$. The arrival of (ω, h) matches is also Poisson with rate $M(u, v)v(\omega)u(h)/(uv)$.

Take a worker of type h. She finds a vacancy with Poisson arrival rate

$$\lambda = M(u, v)/u = M(1, v/u) \equiv m(v/u). \tag{12}$$

We have integrated the arrival rate across all possible vacancy types ω and divided by $u(h)$, because the worker has $1/u(h)$ probability of being the particular type-h worker successfully matched. Notice that the arrival rate of a match is independent of worker type.

Similarly, each vacant position (irrespective of its type ω) is filled with Poisson arrival rate

$$\eta = m(v/u)u/v. \tag{13}$$

We are now ready to define the equilibrium in this economy.

Definition 1 *A* steady-state equilibrium *is (i) a pair of value functions for firms $J(\omega, h)$ and $J_0(\omega)$, (ii) a pair of value functions for workers $V(\omega, h)$ and $V_0(h)$, (iii) matching rates λ and η, (iv) acceptance rules $x_1(\omega, h)$ and $x_2(\omega, h)$ for firms and workers, (v) a joint distribution function $\Gamma(\omega, h)$ of matched firms and workers, (vi) a technology choice rule $\chi(\omega, h)$, and (vii) a wage function $w(\omega, h)$ such that*

1. *firms maximize the present discounted value of expected profits, satisfying equations* (5) *and* (6)*,*

2. *workers maximize the present discounted value of expected wages and benefits, satisfying equations* (3) *and* (4)*,*

3. *firms accept all profitable matches: $x_1(\omega, h) = 1$ if and only if $S(\omega, h) > 0$,*

4. *workers accept all profitable matches: $x_2(\omega, h) = 1$ if and only if $S(\omega, h) > 0$,*

5. *the stock of unemployed at any skill level is constant,*

$$\lambda u(h) \int_\omega x_2(\omega, h) dG_\omega = \delta(L - u) \int_\omega d\Gamma(\omega, h), \tag{14}$$

6. *the stock of vacancies at any productivity level is constant,*

$$\eta v(\omega) \int_h x_1(\omega, h) dG_h = \delta(N - v) \int_h d\Gamma(\omega, h), \tag{15}$$

7. *matching rates λ and η are given by the matching function, satisfying equations* (12) *and* (13)*,*

8. *technology choice maximizes joint surplus, satisfying equation* (1)*,*

9. *workers get a β share of the joint surplus from a match, satisfying equation* (8)*.*

Conditions 1 and 2 ensure that the HJB equations hold. Conditions 3 and 4 define the acceptance rule of firms and workers as a function of the surplus created. Because both parties maximize expected cash flow and utility is transferable via wages, they both have an incentive to accept all matches with positive surplus. Condition 5 states that the outflow of workers from unemployment, which is the product of the arrival rate of matches, the stock of unemployed and the acceptance rate, equals the inflow of workers, which is the exogenous rate of match dissolution times the stock of matches with skill level h. Condition 6 is a similar flow equilibrium for firms. The rest of the equilibrium conditions are self explanatory.

Following Postel-Vinay & Robin (2002), we will focus on the type of equilibria in which all matches produce a positive surplus. In this equilibrium, all matches are accepted by both the firm and worker and remain productive until destroyed exogenously with arrival rate δ. This assumption also ensures that the matching between workers and firms is random and not assortative.

Let $\nu = v/u = \lambda/\eta$ denote the tightness of the labor market. Suppose that firms accept all matches, $x_1 \equiv 1$. Integrate both sides of equation (15) over ω to get

$$\eta v = \delta(N - v).$$

Combining this equation with equations (12) and (13), we get the following equilibrium condition for ν:

$$m(\nu)(L - N) = \delta(N - \nu L). \tag{16}$$

If $L > N$, the left-hand side is strictly increasing in ν, whereas the right-hand side is strictly decreasing. For $\nu = 0$, the left-hand side is zero, whereas the right-hand side is positive. For $\nu = N/L < 1$, the right-hand side is zero, wheres the left-hand side is positive. It follows that there is a unique solution $\nu^* < 1$. Similarly, whenever $L < N$, the unique solution is $\nu^* > 1$.

Denote by λ^* and η^* the unique solution to equations (16) and (12). Let $\phi^D(\omega, h) \equiv A_D F(\omega, h) - R_D$ and $\phi^F(\omega, h) \equiv A_F F(\omega, h) - R_F$. Let $\Phi_h(h) \equiv \int_\omega \phi(\omega, h) dG_\omega(\omega)$ denote the expected output ϕ of a worker h when randomly matched with a firm. Similarly, $\Phi_\omega(\omega) \equiv \int_h \phi(\omega, h) dG_h(h)$. To simplify notation, we introduce $\kappa_1 = \lambda^*\beta/(\rho+\delta+\lambda^*\beta)$ and $\kappa_2 = \eta^*(1-\beta)/[\rho+\delta+\eta^*(1-\beta)]$.

Assumption 1 (Sufficient condition to sustain all matches) *For all ω and h,*

$$\phi^D(\omega, h) \geq \kappa_1 \Phi_h^F(h) + \kappa_2 \Phi_\omega^F(\omega) + (1 - \kappa_1)[b(h) - B]. \tag{17}$$

Assumption 1 ensures that the flow value of a match is always high enough to compensate both agents for their outside options. The assumption holds when ρ and δ are high (agents care relatively more about the present), when λ^* and η^* are low (agents have to wait long for new matches), and when the variation in ϕ is small (so that ϕ is not much different from its average).[16]

Proposition 1 *A steady-state equilibrium exists and is unique.*

[16]The assumption would be violated if there were (ω, h) pairings with much lower than average productivity. These pairings would not be viable matches as they would create a negative surplus.

We prove this and all other statements in the Appendix. The following lemmas provide a crucial starting point.

Lemma 1 *If Assumption 1 holds, then, in equilibrium, unemployed workers accept all job offers, and vacant firms accept all workers:* $x_1(\omega, h) = x_2(\omega, h) = 1$ *for all* ω, h*. Matching is random so that* $\Gamma(\omega, h) = G_\omega(\omega) G_h(h)$*.*

Lemma 2 *Let* $\Phi = \int_\omega \int_h \phi(\omega, h) dG$ *denote the average output of worker-firm units and* $B = \int_h b(h) dG_h(h)$ *denote the average unemployment benefit. The value of unemployment for a type-*h *worker is*

$$V_0(h) = \frac{1}{\rho}\left[\kappa_1 \Phi_h(h) + (1-\kappa_1) b(h) - \frac{\kappa_1\kappa_2(1-\kappa_1)(\Phi - B) - (1-\kappa_2)c}{1-\kappa_1\kappa_2}\right]. \tag{18}$$

The value of a type-ω *vacancy is*

$$J_0(\omega) = \frac{1}{\rho}\left[\kappa_2 \Phi_\omega(\omega) - (1-\kappa_2)c - \frac{\kappa_1\kappa_2(1-\kappa_2)(\Phi + c) + (1-\kappa_1)B}{1-\kappa_1\kappa_2}\right]. \tag{19}$$

The annuity value of an unemployed worker $\rho V_0(h)$ increases in her expected output $\Phi_h(h)$, but at a rate $\kappa_1 < 1$. This is because it takes time for her to find a new job and her bargaining power is less than 1. The annuity value is decreasing in the average output of the economy Φ, but at a rate $\kappa_1\kappa_2(1-\kappa_1)/(1-\kappa_1\kappa_2) < \kappa_1$. This is because when the average output of the economy is higher, the average vacancy is worth more, and the worker has to partially compensate the firm for the outside value of the vacancy.

The following proposition characterizes the equilibrium.

Proposition 2 *In a steady-state equilibrium,*

1. *the value of unemployment is strictly increasing in worker skill,*
2. *the value of a vacancy is strictly increasing in firm productivity,*
3. *conditional on firm productivity, wages increase in worker skill,*
4. *more productive firms are (weakly) more likely to import a machine,*
5. *higher skilled workers are (weakly) more likely to use an imported machine,*
6. *for a given firm productivity, workers using an imported machine earn higher wages.*

In general, importers earn higher wages both because of a causal effect of imports on the output of the worker-firm match and also because more skilled workers self-select into importing. We explain in Subsection 1.6 how these predictions can be taken to the data.[17]

Figure 2 shows the probability that an employed worker with skill level h is using an imported machine. We denote this probability by

$$\mu_h(h) \equiv \Pr_\omega[F(\omega, h) > \theta | h]. \tag{20}$$

[17] Hiroyuki Kasahara & Joel Rodrigue (2008) and László Halpern, Miklós Koren & Adam Szeidl (2015) present structural models in which more productive firms become importers, but imported inputs also increase productivity.

Below a level h_0, the worker has no chance of using the imported technology. Even if she is matched with the most productive firm, they will use the domestic technology. After this cutoff, the import probability is strictly increasing in skill. The relationship between firm productivity and the conditional probability of importing is similar.

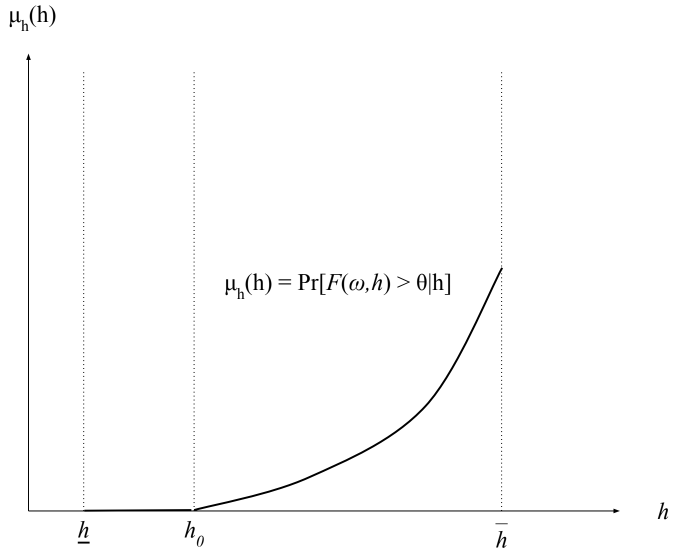

Figure 2: The probability of importing is weakly increasing in worker skill

1.5 Trade liberalization

Trade liberalization reduces the cost of importing machines. This translates into a lower rental cost for imported machines R_F. This reduces the threshold level of production θ above which firms choose to import. Figure 3 shows how this reduction in θ affects technology choice. When θ reduces to θ', it will be optimal for a wider set of firm-worker matches to use an imported machine. Some firms will upgrade to an imported machine even if they hold on to their existing workforce. Similarly, some workers may now be assigned an imported machine even if they stay at the same firm.

To study the effects of trade liberalization, we conduct a comparative static exercise and show how the equilibrium depends on R_F.

Lemma 3 *If Assumption 1 is satisfied, trade liberalization has no effect on the matching rates λ^*, η^*, the stock of workers, firms or matches.*

To ensure that the worker gets a sufficiently large share of the surplus, we assume

Assumption 2 (Worker bargaining power)

$$\frac{\beta}{1-\beta} \geq \frac{\rho+\delta+\eta^*(1-\beta)}{\rho+\delta+\lambda^*\beta}.$$

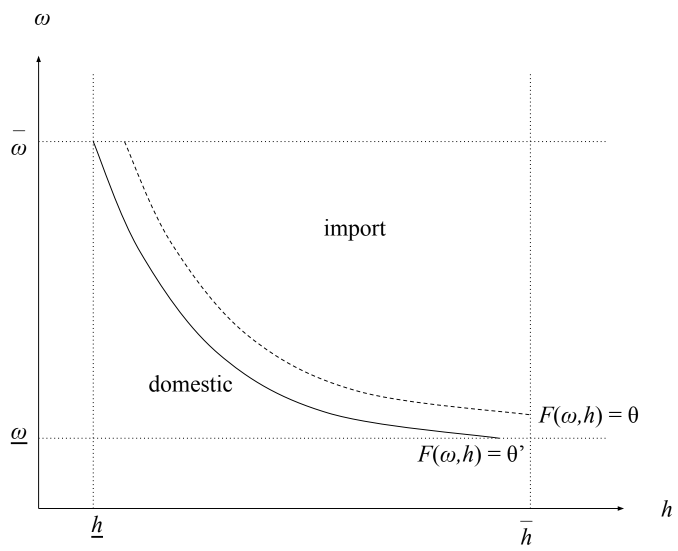

Figure 3: Trade liberalization makes imported machine accessible to a wider set of firm-worker matches

This assumption ensures that if net output $\phi(\omega, h)$ goes up by the same amount for all ω and h, wages increase. It is satisfied in the symmetric case when $\beta = 0.5$, $L = N$, and, hence, $\lambda = \eta$ and $\kappa_1 = \kappa_2$. It is more likely to be satisfied for higher β and lower L/N.

Proposition 3 *When R_F declines,*

1. *more worker-firm matches use an imported a machine,*
2. *the expected return to skill $V_0'(h)$ increases weakly for all h,*
3. *if Assumption 2 holds, the wages of all importer worker-firm matches increase,*
4. *the wage of a non-importer worker-firm match (ω, h) increases if and only if $h > \tilde{h}(\omega) \geq h_0$, where $\tilde{h}$ is weakly increasing in ω.*

Statement 1 follows directly from technology choice as explained in Figure 3. Statement 2 is the result of both the direct effect of importing on wages, but also on the better outside options of high-skilled workers, who now have a higher likelihood of finding a job at an importer.

Statement 3 means that importer wages increase. This follows from importer profits going up and profits being shared with workers. However, workers need to compensate firms for their increased outside option. To ensure that the direct effect of profit sharing is larger, and even the lowest-skilled importer worker enjoys a wage increase, we need Assumption 2.

The intuition for statement 4 is that when a more skilled worker is matched with a less productive firm ($h > \tilde{h}(\omega)$), the worker's outside option increases more with trade liberalizaton than the firm's. Hence the firm has to compensate the worker by offering a higher wage. For less skilled workers at more productive firms, the opposite is true. The firm's outside option increases more, and the worker has to be satisfied with a lower wage.

This proposition yields a testable prediction for non-importers, for whom there is no direct effect on output, and the only effect on wages is via the outside options.

Figure 4 plots the regions of productivities and skills for which trade liberalization increases wages. This region includes all importers and among non-importers those skilled workers that are matched with less productive firms. In the range of productivities and skills for which neither firms nor workers have a chance finding an importer partner, trade liberalization has no effect on outside options and on wages. For low-skill non-importer workers matched with high-productivity firms, the wage effect of trade liberalization is negative. The outside option of firms increases, reducing the surplus of the match, as well as wages.

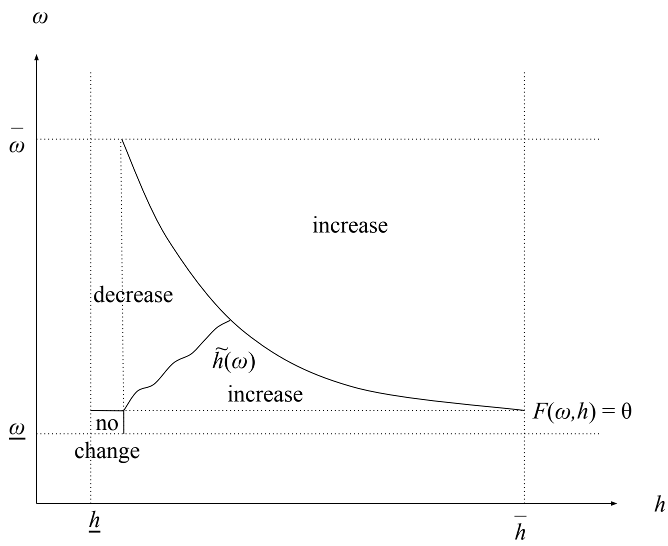

Figure 4: The range of productivities and skills for which trade liberalization increases wages

1.6 Taking the model to the data

In our application, we observe many firms, each with many workers, over several years. The workers are classified in many different occupations, using many different machines. Here we discuss how the model can be adapted to take account of this heterogeneity.

Treatment of time. We treat each year t as a realization of the steady state of the model. That is, any change from year t to $t + 1$ can be thought of as a comparative static exercise in the model. For example, there might be a fall in the cost of imported machines, R_F, resulting in more firm-worker matches importing than before.

This assumption is consistent with rational expectations if all the changes are unforeseen and expected to remain permanent. Alternatively, we can think of it as an approximation of the dynamic adjustment. The approximation will be more accurate if time passes fast, that is, when matches form and dissolve quickly (λ, η and δ high) and agents discount the future heavily (ρ high).[18]

Multi-worker firms. In the data, many workers work at the same firm, whereas our model features unitary worker-firm matches. To reconcile the model with the data in the simplest possible way, we think of a firm of productivity ω as a random collection of worker-firm production units. That is, there are no economies or diseconomies of scale within firms. The identity of a firm is only a label which indexes its productivity. Firm A might have a productivity 1.2 in all of its production units, whereas firm B has a productivity 0.8.

For example, Figure 5 shows a firm with six workers and a productivity level ω_0. The workers represent a random sample of matches with type-ω_0 firms, each with potentially different level of skill h. As shown in Figure 5, two workers will be below the import cutoff and work on domestic machines, while four workers will work on imported machines.

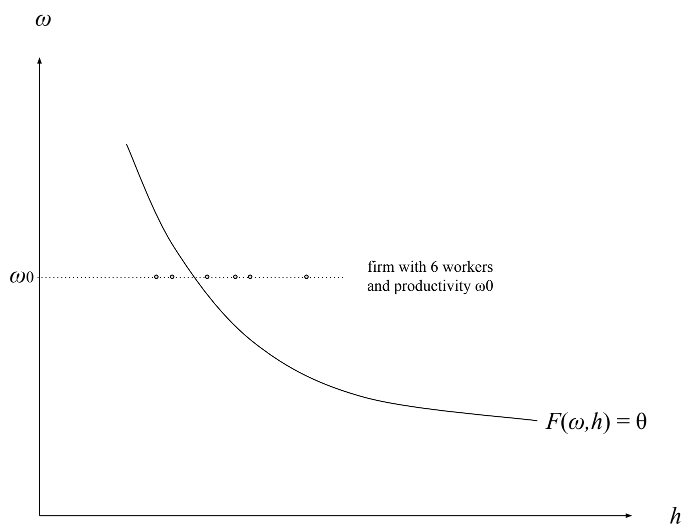

Figure 5: Firms are collections of heterogeneous workers

Modeling firms this way allows for within-firm heterogeneity, which is a key feature of the data. Workers within the same firm receive different wages. Some of them work on imported machines, some work on domestic machines. In our model, workers within the same firm differ in their skill. A distribution of different skills emerges because search frictions prevent the firm from hiring only the best possible match. We believe this assumption captures a salient feature of the job market where search and hiring costs are large and workers very heterogeneous skills hold otherwise similar jobs.[19]

[18] For a model with full transitional dynamics, see Kerem A Cosar, Nezih Guner & James Tybout (2016).

[19] For alternative treatments of multi-worker firms, see Helpman & Itskhoki (2010) and

One implication of this assumption is that firm size is independent of the other sources of heterogeneity in productivity and skill.[20] The assumption is standard (although often not made explicit) in models with constant returns to scale, where firm sizes are indeterminate. A size-10 firm is just a random collection of 10 size-1 firms. We also note that similarly strong knife-edge assumptions have been made before in models where firm sizes is a deterministic function of firm productivity (Melitz 2003).

Different occupations and machines. We observe firms employing machine operators in different occupations, for example, in food processing, packaging and transportation. For simplicity, we think of each occupation as a separate labor market with a fixed supply of workers and skills. For occupation o, the total mass of available workers is L_o. Because occupations have different labor markets, they also have different outside options V_{0o}. We also let the technology parameters A_i and machine prices R_i be specific to occupations. This reflects the fact that the quality and price gap of imported machines might be vastly different in the food industry and in packaging, say.

Estimating equation. Taken together, these assumptions imply that the wage of a worker i at firm f in occupation o in year t is

$$w_{ifot} = \tilde{\phi}_{ot}(\omega_{ft}, h_i) + \chi_{ifot}\Delta\phi_{ot}(\omega_{ft}, h_i) + \tilde{V}_{ot}(h_i) - \tilde{J}_{ft}, \tag{21}$$

where $\tilde{\phi}_{ot}(\omega, h) = \beta[A_{Dot}F(\omega, h) - R_{Dot}]$ is the wage component from worker productivity on a domestic machine, $\Delta\phi_{ot}(\omega, h) = \beta(A_{Fot} - A_{Dot})[F(\omega, h) - \theta_{ot}]$ is the productivity premium of importing (see equation (2)), $\tilde{V}_{ot}() = (1 - \beta)\rho V_{0ot}()$, and $\tilde{J}_{ft} = \beta\rho J_0(\omega_{ft})$. The production function varies by occupation and time and depends on a time varying firm productivity and a time invariant worker skill. The outside option of worker varies by occupation and time and depends on her skill. The outside option of the firm depends on the firm and the year.

To construct a feasible estimable equation, assume that production is Cobb–Douglas, $F(\omega, h) = \omega^\alpha h^{1-\alpha}$, and approximate (21) loglinearly around a marginal non-importer firm, (ω_n, h_n), for whom $\Delta\phi_{ot}(\omega_n, h_n) = 0$:

$$\begin{aligned}\ln w_{ifot} \approx C_0 + C_1[\ln A_{Dot} + \alpha \ln \omega_{ft} + (1-\alpha)\ln h_i)] - C_2 \ln R_{Dot} \\ + C_3\chi_{ifot}\Delta\phi_{ot}(\omega, h) + C_4 \ln \tilde{V}_{ot}(h_i) - C_5 \ln \tilde{J}_{ft} + \varepsilon_{ifot},\end{aligned} \tag{22}$$

with C_0 through C_5 positive constants, and ε_{ifot} capturing terms of second or higher order.[21]

Wages depend on occupation-specific terms $(C_1 \ln A_{Dot} - C_2 \ln R_{Dot})$, firm specific terms $(C_1\alpha \ln \omega_{ft} - C_5 \ln \tilde{J}_{ft})$, skill specific terms $(C_1(1-\alpha)\ln h_i + C_4 \ln \tilde{V}_{ot}(h_i))$, import behavior, and higher order approximation errors. We are interested in the treatment effect $C_3\Delta\phi_{ot}(\omega_{ft}, h_i)$ among importers. Note

Daron Acemoglu & William B Hawkins (2014).

[20] Although it is straightforward to build in an exogenous dependence of firm size n and firm productivity ω.

[21] Neither the Cobb–Douglas assumption, nor the loglinear approximation are necessary for the qualitative statements of the model. They merely make empirical estimation more convenient.

that this is heterogeneous, with more productive firms and more skilled workers enjoying higher wage gains from importing. We will estimate both the average wage premium associated with importing and how importing increases the returns to skill.

The challenge in estimating (22) is that firm productivity, worker skill, as well as outside options are unobserved. Moreover, they are correlated with the choice to import χ_{ifot}, as shown in equation (1). We address these problems in three ways. First, we include rich controls for worker and firm observables. Second, we control nonparametrically for both worker skill and firm productivity. Third, we instrument import choice with variables that are plausibly uncorrelated with both unobservables.

2 Data

We use Hungarian linked employer-employee data from 1992-2003 to evaluate the predictions of the model. In this time period, after the fall of communism in 1989 and before joining the European Union in 2004, Hungary witnessed rapid import liberalization. An additional benefit of our application is the richness of the data, which permits us to focus on operators of specialized manufacturing machinery, who are most likely to be directly affected by machinery imports.

Employee data come from the Hungarian Structure of Earnings Survey (*Bértarifa*), which contains a 6 percent quasi-random sample of all employees (10 percent for white-collar workers), recording their earnings, 4-digit occupation, education, age and gender. We use the annual waves between 1992 and 2003. 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).

We restrict our attention to 53 machine operator occupations, representing about 10 percent of the workforce in the private sector. Because sampling is different for small firms, we drop all firms below 20 employees. We are left with 87,489 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.[22] For each worker in *Bértarifa*, we can precisely identify the international transactions of his/her employer. In particular, not only do we see whether the employer imported any machinery in the past, we also see the specific equipment goods that it imported. We restrict our attention to 290 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

[22] Halpern, Koren & Szeidl (2015) provide more details on the Hungarian Customs Statistics dataset.

can be used by a wide range of workers, not only machine operators. Around one third of all imports of machinery, vehicles and instruments is spent on such specialized machines.

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. Because we cannot observe firm productivity, we use these as controls in our wage regressions.

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 "Phototypesetting and composing machines" (HS code 844210), as well as with "Reel fed offset printing machinery" (844311), but not with "Machines for weaving fabric, width < 30 cm" (844610). Note that this is a many-to-many match: the average occupation is associated with 7.04 different type of machines, and the average machine is associated with 1.29 occupations. The Appendix provides the details of this matching procedure.

For each worker in each year, we create a measure of access to imported machinery, which takes the value of one if the employer imported machine(s) specific to the worker's occupation any time in the past, and zero otherwise.[23]

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

Second, we do not know *which worker* within the specific occupation received the machine. If there are multiple machine operators in the same occupation at the same firm and only one of them is assigned the machine, we will wrongly classify the others as importers. 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.

3 Patterns of imports and wages

3.1 Import trends

Table 1 shows the number of workers and firms in our estimation sample over time. The sample is growing somewhat as more and more firms enter the survey and as they expand. Between about 20 and 70 percent of workers are exposed to imported machines, and this trend is clearly increasing over time. The third column reports the simple fraction of workers importing. Because the sampling rules change over time, this number is not representative of the overall import

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

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 1: The estimation sample over time

Year	Workers	Firms	Fraction importing (percent)	Import exposure (percent)
1992	3,965	754	42.85	21.00
1993	4,287	918	49.57	30.05
1994	4,655	888	49.90	35.29
1995	5,329	1,014	56.65	40.45
1996	5,111	984	61.04	44.52
1997	4,697	914	65.21	47.97
1998	5,445	1,008	68.04	52.55
1999	5,186	997	70.52	54.64
2000	5,760	1,100	68.91	56.90
2001	5,913	1,077	71.01	59.28
2002	5,554	1,002	69.55	60.43
2003	5,271	950	69.17	61.21

Notes: "Fraction importing" denotes the fraction of workers in the sample exposed to an imported machine in their occupation-firm-year cell. "Import exposure" is defined on a balanced sample of firm-occupations and denotes the fraction of workers importing in this balanced sample.

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

We use annual data on the book value of machines and machine imports to construct a panel of machine purchases and a measure of vintages at the firm.[24] We first calculate nominal net investment flows for each firm for each year as the difference between the book value of equipment in consequtive years plus the amount of depreciation. If the net investment flow is positive, we treat it as gross investment (with zero disinvestment) into new vintages in that particular year. Similarly, if the net investment is negative, we treat it as pure disinvestment: the selling of the oldest possible vintage at the firm. Whenever imports are higher than net investment, we infer that the firm concurrently installed new imported machines and sold equipment of an old vintage.

The result is a panel of gross investment and disinvestment flows by vintage (imputed year of purchase), separately for domestic and for imported machines.

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

We cumulate these flows to construct a stock of vintages after deflating nominal flows by the overall machinery price index, separately for domestic and imported machines.

Table 2 presents the share of capital stock in each vintage for the year 2003. Capital stock is skewed towards later vintages, with a somewhat higher share coming from the first year of the sample.[25] The share of imports increases from 11.96 percent in the 1992 vintage to 68.41 percent in the 2003 vintage.

Table 2: The vintages of capital stock

Vintage	Machine stock (percent)	Imported (percent)
1992	8.88	11.96
1993	2.79	28.42
1994	3.42	34.73
1995	3.53	33.43
1996	3.85	34.79
1997	5.32	32.50
1998	6.29	38.37
1999	7.62	43.19
2000	9.92	37.23
2001	12.43	49.51
2002	15.25	57.76
2003	20.71	68.41

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

We next study how import behavior is correlated with tariffs. Tariffs on imported machinery have significantly declined in the 1990s. (See Table 3.) 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.[26] Given the relatively little economic weight of Hungary relative to the EEC, we can think of these tariff changes as exogenous from the point of view of Hungarian producers.

We begin by creating occupation-specific tariff rates for each year, as the average of statutory tariff rate on machines associated with the occupation. For each machine, and hence for each occupation, we have two tariff rates: those on imports from the EEC (which we call "EU tariffs"), and Column 2 tariffs. For example, the average EU tariff of machines used by textile machine operators was 2.8 percent in 1996. The Column 2 tariff for the same goods in the same period was 8.8 percent.

Figure 6 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 weak negative association between tariff change and import adoption. Each

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

[26] 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 3: Average machinery tariffs

Year	Tariff on EU imports	Column 2 tariff
1992	8.97	9.28
1993	8.58	9.19
1994	8.27	9.19
1995	5.52	8.79
1996	3.13	9.00
1997	0.709	8.78
1998	0.524	8.54
1999	0.325	8.31
2000	0.162	8.31
2001	0.000	8.29
2002	0.000	8.32
2003	0.000	8.28

Notes: Table reports the unweighted average of machinery tariffs on 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.

percentage point reduction in tariffs from the EU is associated with a 1.35 percentage point increase in imports. We explore this relationship further in an instrumental variable strategy in Section 4.2.

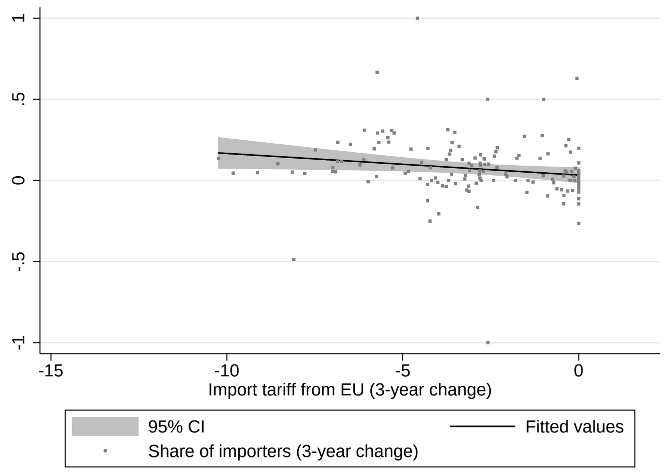

Figure 6: Occupations with faster tariff cuts adopted imported machines faster

3.2 Wages and the return to skill

Table 4 reports the the percentage wage gap between various groups of workers over time. The second column shows the percentage wage difference associated with a high-school degree (relative to primary school and vocational school), controlling for worker gender, age and occupation. The third column shows the percentage difference between the 90th and 10th percentile of the within-occupation wage distribution.

Table 4: Wage inequality over time

Year	High-school premium	90/10 inequality
1992	11.45	156
1993	11.79	168
1994	11.63	173
1995	12.56	165
1996	13.54	180
1997	12.84	199
1998	17.71	204
1999	16.77	209
2000	14.30	199
2001	10.69	173
2002	13.35	166
2003	10.00	173

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

The minimum wage has been 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 11.45 percent in 1992 to 14.30 percent in 2000. Similarly, the wage gap between the 90th and the 10th percentile of the within-occupation wage distribution has widened from 156 percent to 199 percent.

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

To construct a model-consistent, continuous measure of skill, we study how wages are correlated with worker observables. We first calculate the ranking of each worker in the wage distribution of their occupation in the given year. Let $p_{iot} \in [0,1]$ denote the quantile of worker i in occupation o in year t. For the highest-paid worker in the occupation-year, $p_{iot} = 1$.[27] We then regress p_{iot} on time invariant worker observables X_i, separately for each year,

$$\hat{p}_{it} = E_t(p_{iot}|X_i). \tag{23}$$

These observables include the worker's gender, education, year of birth, occupation, and the interaction of all these indicators. The wage distribution changes year to year (for example, because of changes in the minimum wage), so we estimate the relationship between wage percentiles and worker observables separately for each year. The resulting measure of skill $\hat{p}_{it}$ does not depend on firm

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

characteristics. It takes values between 0 and 1, with higher values representing higher expected earnings.

We use the predicted quantile of the wage distribution, rather than the wage itself, to measure worker skill. This is because we want to study how the returns to skill changed over time. For example, we can compare the wages of workers with predicted quantiles 0.98 and 0.99 to estimate how the returns to skill have changed at the upper end of the distribution.

Specifically, we estimate the following wage equation.

$$\ln w_{ifot} = V_t(\hat{p}_{it}) + \alpha X_{ft} + \mu_o + \nu_t + u_{ifot} \tag{24}$$

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

In practice, we estimate $V_t()$ as a spline function of $\hat{p}_{it}$ using cubic splines with knots at $\hat{p}_i = 0.25, 0.4, 0.6, 0.75, 0.9$. (Using quantiles of $\hat{p}_{it}$ or locally weighted regressions yields similar results.) The vector X_{ft} includes the log capital stock of the firm, indicators for majority foreign ownership and whether the firm has imported before, and quadratic functions of log firm employment and firm age.

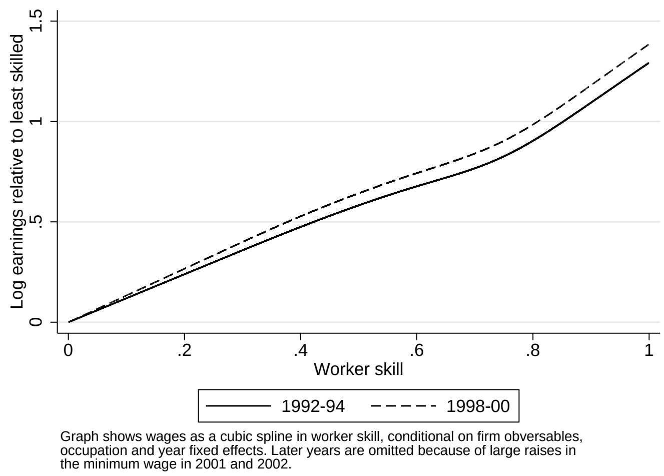

Figure 7: The return to skill has increased throughout the distribution

Figure 7 plots our estimated V_t function. With a suitable normalization we set $V_t(0) = 0$, so that we can compare wages to workers with the lowest level of skill. Note that wages are monotonically increasing in skill and that the relationship is much steeper in the late period than in the early period. That is, the return to skill has increased substantially between 1992 and 2000.

In the early period, the most skilled worker makes 264 percent more than the least skilled worker in the same occupation at a similar firm. This wage gap widens to 299 percent in the later period. Relative to the least skilled worker, the wage of the most skilled worker goes up by 9.68 percent.

That is, the increase in inequality reported in Table 4 is pervasive throughout the entire wage distribution. We later quantify what fraction of this increase can be attributed to machinery imports.

3.3 When do firms import?

The model made predictions about which firms import and how this depends on the cost of imported machinery. Table 1 showed that, over time, more and more workers are exposed to imports. We also saw in Table 2 that firms have increased the share of imported machinery in their capital stock. In this section we study the determinants of importing in more detail. We then develop an instrumental variable strategy based on exogenous declines in import tariff rates.

We look at the data through the lens of the model. Let χ_{ft} denote whether a firm f 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 proportional hazard model, where the hazard of starting to import depends proportionally on a hazard function ν_t and exponentially on firm controls:

$$\zeta_{ft} = \nu_t \exp[\alpha X_{ft}]. \tag{25}$$

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

In discrete time, the hazard function leads to the following estimating equation

$$\Pr(\chi_{ft} = 1 | \chi_{f,t-1} = 0) = 1 - e^{-\zeta_{ft}} = 1 - e^{-e^{\ln \nu_t + \alpha X_{ft}}}, \tag{26}$$

which can be estimated by maximum likelihood using a complementary log-log regression.

The first two columns of Table 5 report the results of two firm-year hazard regressions. In column 1, we let the hazard of importing depend on log capital stock, foreign ownership, and other controls. We find that firms with more capital and foreign firms are more likely to start importing in any given year.

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

Having older vintages increases the hazard of importing. A firm that has purchased all of its equipment 6 or more years ago is 1.64 times as likely to import than a firm with only recent (0-1-year) investment. This suggests that firms tend to replace older vintages of capital. For simplicity, and because we have a very rudimentary estimate of capital vintage, our model does not capture the dynamic nature of machinery choice.

Columns 3 and 4 report regressions at the firm-occupation-year level. Column 3 only reestimates specification 1 at the firm-occupation-year level, finding similar correlations between capital stock, foreign ownership, and the hazard of importing.

In Column 4, we control for the level of tariffs. We calculate the relevant tariff as the average tariff facing EU imports for machines relevant to the given

Table 5: When do firms start importing?

	(1) Hazard of importing	(2) Controlling for vintage	(3) Occupation level	(4) Tariff interactions
Book value of machinery	0.246***	0.247***	0.361***	0.357***
(log)	(0.028)	(0.028)	(0.018)	(0.018)
Firm is foreign owned	1.05***	1.05***	0.953***	0.970***
(dummy)	(0.083)	(0.084)	(0.045)	(0.057)
Equipment bought 2–5		0.289***		
years ago (share)		(0.093)		
Equipment bought 6 or		0.495*		
more years ago (share)		(0.257)		
EU tariff				-0.033***
× employment (log)				(0.010)
EU tariff				0.004***
× employment (log, squared)				(0.001)
Number of observations	4,593	4,593	13,187	13,187

Notes: The dependent variable is an indicator for importer status. All regressions estimate a complementary log-log specification for the hazard of starting to import. Firm controls include quadratic functions of log employment and 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.

occupation in the given year.[28] 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. It also suggests that firms in the middle of the productivity distribution are especially likely to change their import behavior in response to tariff changes. Less productive firms may still not recoup the cost of an imported machine, and more productive firms might already be importers. We hence interact tariff rates with a quadratic function of firm employment (as a proxy for productivity) to predict which firms will start importing.

We can augment our hazard model to depend proportionally on an occupation-specific hazard function ν_{ot} and exponentially on tariffs τ_{ot}^{EU}, interacted with firm size:

$$\zeta_{fot} = \nu_{ot} \exp[\alpha X_{ft} + \tau_{ot}^{\mathrm{EU}}(\gamma_0 + \gamma_1 \ln L_{ft} + \gamma_2 \ln L_{ft}^2)]. \tag{27}$$

Note that γ_0, the direct effect of tariffs, cannot be identified separately from ν_{ot}, so we assume it to be zero. In practice, it will be soaked by occupation-year

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

fixed effects. The identification of γ_1 and γ_2 comes from whether large and medium-sized firms respond more to tariffs than small ones.

Column 4 of Table 5 reports the estimated γ_1 and γ_2 coeffients from the hazard model. If firms of intermediate size are most likely to start importing when tariffs decline, we expect $\gamma_1 < 0$ and $\gamma_2 > 0$. This is indeed what we find.

If tariffs decline by 1 percentage point, then, relative to a 1-employee firm, a firm with 10 employees is 5.48 percent more likely to start importing, whereas a firm with 100 employees is 6.27 percent more likely. The hazard of importing after a tariff decline initially increases with firm size, but at a diminishing rate. Indeed, the hazard is highest at an intermediate size, with 46.07 employees. The exclusion test of these tariff-firm-size interactions yield a p-value of 0.000.

3.4 Which workers import?

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

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

Figure 8 displays the distribution of our skill index in these three categories for the first five years of the sample. Consistently with the model, high-skilled workers are overrepresented among early importers. Late importers have a balanced distribution of skill, whereas workers that never import tend to be of a lower skill.

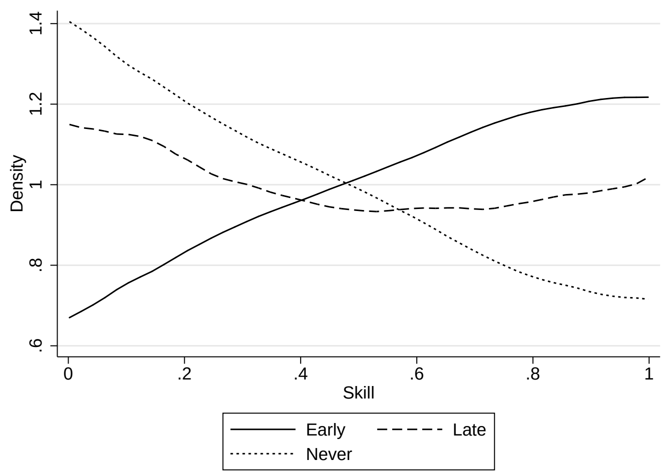

Figure 8: Among early importers, high-skill workers are overrepresented

4 The effect of import exposure on wages

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

4.1 Implementation

Collect terms from equation (22)

$$\ln w_{ifot} \approx C_3 \chi_{ifot} \Delta\phi_{ot}(\omega, h) + C_4 \ln \tilde{V}_{ot}(h_i) + u_{ot} + u_{ft} + \varepsilon_{ifot}, \tag{28}$$

where $\ln w_{ifot}$ is the log monthly earnings of worker i at firm f in occupation o in year t, χ_{fot} is an indicator taking the value one if the firm has imported the machine necessary for occupation o by time t. We are interested in the average treatment effect of importers, $\xi = C_3 E[\Delta\phi_{ot}(\omega, h)]$.

The remainder of the wage equation can either be captured by controls or subsumed in the error term. Specifically, we always control for the education, gender, age (in quadratic form) and occupation 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_{fot}, because this latter also varies across occupations.

To capture the outside option of workers, $\tilde{V}_{ot}(h_i)$, we adopt the following nonparametric strategy. We create an index of skill by predicting a worker's place in the wage distribution based on their gender, occupation, education and year of birth, including all their interactions. This index is described in detail in Section 3.4. We then control for a cubic spline of this skill index in the wage equation. Because the return to skill might vary across occupations and over time, we let the spline coefficients vary aross broad occupations and over time, resulting in $V_{ot}(\hat{p}_{it})$, our proxy for $\tilde{V}_{ot}(h_i)$.

To better capture the selection effect that more productive firms are more likely to import (Proposition 2), we also report results with firm-year fixed effects. We also instrument for machine imports, as outlined below.

Table 6 reports the estimated treatment effects together with standard errors clustered by firm. The baseline specification in column 1 yields an estimate ξ of 0.055, which means that workers exposed to imported machines earn 5.63 percent more than similar workers at similar firms using only domestic machines. The estimated treatment effect reduces to 3.51 percent with nonparametric skill controls and to 2.14 percent with both skill controls and firm fixed effects.[29]

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.

[29] These returns are roughly one third of the returns to having a high school education. 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, Jayaraman & Trépanier (2010).

Table 6: The effect of import exposure on wages

	(1) Baseline	(2) Skill controls	(3) Firm controls	(4) IV
Worker exposed to imported machine (dummy)	0.055***	0.035***	0.021**	0.321***
	(0.016)	(0.010)	(0.011)	(0.066)
Firm is an importer (dummy)	0.019	0.011		-0.056
	(0.017)	(0.011)		(0.144)
Firm is foreign owned (dummy)	0.127***	0.075***		0.095**
	(0.017)	(0.011)		(0.024)
Book value of machinery (log)	0.086***	0.049***		0.072***
	(0.006)	(0.005)		(0.012)
R^2	0.517	0.715	0.863	0.496
Number of observations	61,173	61,173	61,173	61,173
Worker controls	Baseline	Baseline+ spline of skill	Baseline+ spline of skill	Baseline
Firm controls	Baseline	Baseline	Firm-year FEs	Baseline
Instruments				Predicted import probability
F-test for 1st stage				76.77

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. Worker controls include indicators for gender and schooling and a quadratic function of worker age. Firm controls include quadratic functions of log employment and firm age. In column 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 column 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.

4.2 Instrumenting imports with tariffs

As suggested by the model, firms that use imported machinery differ in unobserved productivity. To identify the causal effect of importing on wages, we need exogenous variation in firm import behavior. We follow Pinelopi Koujianou Goldberg, Amit Kumar Khandelwal, Nina Pavcnik & Petia Topalova (2010) and Kasahara, Liang & Rodrigue (2013), and exploit a large trade liberalization episode, namely, Hungary's accession to the EU. As described in Section 3.1, 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 f 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 (27). Because large and medium-sized firms are more likely to start importing, they will respond more to a given decrease in tariffs. This is indeed what we found in Section 3.3.

Taking the predicted value from equation (27) as

$$\hat{\zeta}_{fot} \equiv \hat{\nu}_{ot} \exp[\tau_{ot}^{\mathrm{EU}}(\hat{\gamma}_1 \ln L_{ft} + \hat{\gamma}_2 \ln L_{ft}^2)],$$

we have an estimated hazard of importing. We then calculate the predicted probability of a firm having imported by time t as

$$\hat{\pi}_{fot} = 1 - e^{-\sum_{s=b_f}^{t} \hat{\zeta}_{fos}},$$

where b_f 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 $\hat{\pi}_{fot}$ as an instrument for χ_{fot}. We similarly construct an instrument for firm-level imports. Because $\hat{\pi}_{fot}$ is increasing in the firm's age, we control for a quadratic function of firm age in all regressions.

Table 7: Predicted and actual importing

	(1) Firm-occupation import	(2) Firm import
Predicted probability of firm-occupation importing	0.547***	-0.013**
	(0.036)	(0.021)
Predicted probability of firm importing	-0.084***	0.239***
	(0.028)	(0.024)
Book value of machinery (log)	0.039***	0.042***
	(0.004)	(0.005)
Firm is foreign owned (dummy)	0.049***	0.028***
	(0.013)	(0.011)
R^2	0.508	0.367
Number of observations	61,173	61,173
F-test for excluding instruments	76.77	52.10

Notes: The dependent variable is an indicator for importer status. All regressions estimated by ordinary least squares and control for occupation-year fixed effects. Worker controls include indicators for gender and schooling and a quadratic function of worker age. Firm controls include quadratic functions of log employment and firm 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 7 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 76.77. The association is weaker, but still strongly significant at the firm-level. That is, our instruments generate sufficient variation in both the firm-occupation- and the firm-level import indicator.

As Column 4 of Table 6 shows, the IV estimate of the effect of imported machine on operator wages is 0.321. 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.

4.3 General equilibrium effects

We now turn to testing two predictions of Proposition of 3. First, that trade liberalization increases the return to skill. Second that wages for a subset of workers increase when *others* start importing. This is because the outside options of these workers become more attractive.

Column 1 of Table 8 reports the return to a high-school degree in the full sample of machines operators. We interact the indicator for a high-school degree with the fraction of workers in the occupation that are already importing in that given year. We expect this interaction to have a positive effect on wages, which is what we find. Indeed, in occupation-years with no importers, the return to a high-school degree is 4.60 percent. By contrast, in an occupation-year where half of the workers are already importing, the return to high school is 10.90 percent. That is, larger exposure to importing in the labor market is associated with higher return to education.

Table 8: General equilibrium effects on wages

	(1) Returns to HS	(2) Nonimporters	(3) Full sample
Worker exposed to imported machine (dummy)			0.021
			(0.022)
Firm is an importer (dummy)	0.028**	0.020	0.007
	(0.013)	(0.014)	(0.014)
Fraction of workers importing	0.083	0.053	0.056
	(0.052)	(0.078)	(0.064)
Worker completed high school (dummy)	0.045***	0.047***	0.110***
	(0.014)	(0.017)	(0.010)
Fraction importing × high school	0.117***	0.085*	
	(0.029)	(0.043)	
Fraction importing × importer			0.063
			(0.047)
Fraction importing × skilled nonimporter			0.089**
			(0.043)
R^2	0.437	0.377	0.439
Number of observations	61,173	22,785	61,173

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. Worker controls include indicators for gender and schooling and a quadratic function of worker age. Firm controls include log book value of machinery, an indicator whether the firm is foreign owned and quadratic functions of log employment and firm age. 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.

To study the return to skill in more detail, we use the continuous measure of skill we constructed in Section 3.2. Recall that this measure is based on worker observables that are correlated with higher wages (including education, age, gender and occupation). We estimate a specification similar to the one reported in Column 1 with the exception that skill is now captured by a cubic spline of our skill index.

Figure 9 plots the return to skill for two values of import exposure. Low import exposure means that 25.51 percent of workers import in the occupation-year cell. This ratio corresponds to the weighted average of import exposure in 1992-94. High import exposure means 51.43 percent of workers importing, corresponding to the average of 1998-2000.

For both groups, we plot their estimated wages relative to the least skilled worker, after having conditioned on other worker and firm observables. (See Section 3.2 for details.) Within high-import occupations, we see a pervasive increase in the slope of wages with skill, that is, the return to skill. The wage difference between the highest- and lowest-skill workers is 2.64 percent more under high than under low import exposure. This represents more than one quarter of the increase in the return to skill during our sample period.

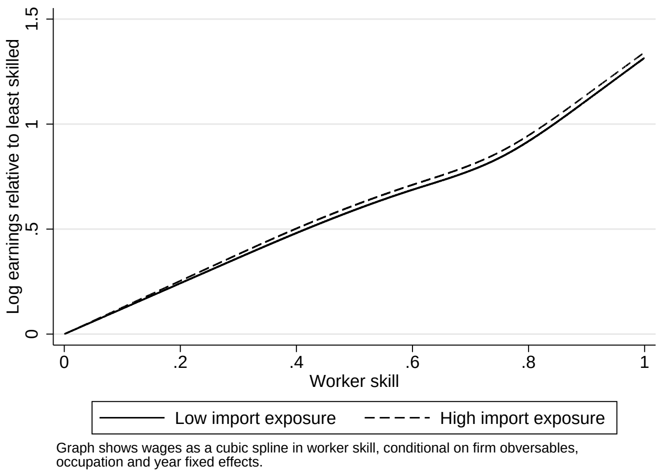

Figure 9: The return to skill increases with import exposure

The rest of Table 8 tests the prediction that other workers' import behavior has a general equilibrium effect on wages. In Column 2, we study non-importers. Recall from Proposition 3 and Figure 4 that among non-importers, skilled workers are more likely to see a wage increase after trade liberalization. Indeed, we find that for high school graduates, a larger fraction of workers importing is associated with higher wages. Remember that these workers are not importing themselves. There is no such association for unskilled workers. In other words, trade liberalization also raises the return to skill for non-importers.

In Column 3 we test whether trade liberalization (as captured by the average importer share in the occupation-year) is also associated with higher wages for importers, as predicted by Proposition 3. We interact the fraction of importing workers with two indicators: one for workers that already import and one for skilled non-importers. Recall from Figure 4 that both groups should see a wage increase. Indeed, we find a positive coefficient for both interactions, although only the one for skilled non-importers is significant.

4.4 Robustness

Table 9 reports the results of wage regressions with various number of firm controls. Column 1 report a specification with only worker controls and no firm controls at all. In this specification, we are comparing the wages of importer workers to those of similar non-importer workers. Workers at importing firms earn 20.20 percent more than similar workers at non-importing firms. If the imported machine is specific to their occupation, they earn an additional 20.28 percent more. As we see below, most of these large differences can be attributed to the selection of firms into importing.

Table 9: Robustness to various firm controls

	(1) No firm controls	(2) Capital stock	(3) Vintage	(4) Full controls
Worker exposed to imported machine (dummy)	0.185***	0.080***	0.080***	0.055***
	(0.020)	(0.016)	(0.016)	(0.016)
Firm is an importer (dummy)	0.184***	0.039**	0.037**	0.017
	(0.019)	(0.018)	(0.018)	(0.017)
Book value of machinery (log)		0.073***	0.073***	0.086***
		(0.006)	(0.006)	(0.006)
Equipment bought 2–5 years ago (share)			0.000	0.007
			(0.019)	(0.020)
Equipment bought 6 or more years ago (share)			0.086**	0.060
			(0.038)	(0.043)
Firm is foreign owned (dummy)				0.129***
				(0.018)
R^2	0.421	0.491	0.492	0.517
Number of observations	61,173	61,173	61,173	61,173

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. Worker controls include indicators for gender and schooling and a quadratic function of worker age. In column 4, full controls include quadratic functions of 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.

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 8.38 percent and the wage premium of importing firms becomes insignificant.

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. Surprisingly, older vintages are associated with higher wages. This may be due to firm selection: firms having invested 6 or more years ago might be mature, successful firms.

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, and quadratic functions of firm size and age (not reported). We also include the vintage composition of capital. The estimated wage premium drops to 5.65 percent, but is still strongly significant. Recall that once we include firm-year fixed effects, which soak up the effect of any firm control, our estimate of the wage effect is 2.14 percent (Table 6).

Appendix B and D contain further robustness checks.

5 Conclusions

We showed in Hungarian linked employer-employee data for 1992-2003 that machine operators exposed to imported machines earn higher wages than similar workers at similar firms. The wage import premium only applies to occupations related to the specific machine imported by the firm. Using product-specific tariff rates as instruments for importing suggests that the importer wage premium is causal. The returns to skill have increased in our sample between 1992 and 2000. A quarter of the increase can be attributed to greater exposure to imported machines. We built a model to to explain which workers and firms use imported machines and how this affects wages. Our results suggests that imported machines can help propagate skill-biased technical change.

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

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

Third, the skill-biased nature of imported machines could be endogenized in a model of directed technical change (Daron Acemoglu 1998, Daron Acemoglu 2002) and appropriate technology (Susanto Basu & David N 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: Proofs

A.1 Proof of Lemma 1

For this lemma to hold, we need $S(\omega, h) \geq 0$ for all ω and h. Then it is clearly optimal for all workers and firms to accept all matches. Because all matches are accepted and separation is exogenous, the distribution of worker skill h will be the same for each type of firm ω, and the same as the distribution of skills in the population $G_h(h)$.

Given the formula for the surplus (11), we need to show that

$$\phi(\omega, h) \geq \rho[V_0(h) + J_0(\omega)],$$

and the right-hand side can be written as

$$\kappa_1 \left[\Phi_h(h) - \frac{\kappa_2(1-\kappa_1)}{1-\kappa_1\kappa_2}\Phi\right] + \kappa_2 \left[\Phi_\omega(\omega) - \frac{\kappa_1(1-\kappa_2)}{1-\kappa_1\kappa_2}\Phi\right] + (1-\kappa_1)[b(h) - B].$$

This term is less than

$$\kappa_1 \Phi_h^F(h) + \kappa_2 \Phi_\omega^F(\omega) + (1-\kappa_1)[b(h) - B],$$

which, by Assumption 1 is less than $\phi(\omega, h) \geq \phi^D(\omega, h)$.

A.2 Proof of Lemma 2

Let $H = \int_h V_0(h) dG_h(h)$ be the average expected value of being unemployed and $\Omega = \int_\omega J_0(\omega) dG_\omega(\omega)$ be the expected value of a vacancy.

Combining equations (3), (8) and (11), we write worker value as

$$V_0(h) = \frac{1}{\rho}\left[\kappa_1 \Phi_h(h) + (1-\kappa_1) b(h)\right] - \kappa_1 \Omega. \tag{29}$$

Similarly, equations (5), (9) and (11), lead to

$$J_0(\omega) = \frac{1}{\rho}\left[\kappa_2 \int_h \phi(\omega, h) dG_h(h) - (1-\kappa_2)c\right] - \kappa_2 H. \tag{30}$$

Averaging the two equations across h and ω, respectively, we get

$$H = \frac{1}{\rho}\left[\kappa_1 \Phi + (1-\kappa_1)B\right] - \kappa_1 \Omega,$$

and

$$\Omega = \frac{1}{\rho}\left[\kappa_2 \Phi - (1-\kappa_2)c\right] - \kappa_2 H,$$

Solving these two equations for H and Ω,

$$H = \frac{\kappa_1(1-\kappa_2)(\Phi + c) + (1-\kappa_1)B}{\rho(1-\kappa_1\kappa_2)}, \tag{31}$$

$$\Omega = \frac{\kappa_2(1-\kappa_1)(\Phi - B) - (1-\kappa_2)c}{\rho(1-\kappa_1\kappa_2)}. \tag{32}$$

Then we can write

$$\rho V_0(h) = \kappa_1 \Phi_h(h) + (1-\kappa_1) b(h) - \frac{\kappa_1\kappa_2(1-\kappa_1)(\Phi - B) - (1-\kappa_2)c}{1-\kappa_1\kappa_2}. \tag{33}$$

and

$$\rho J_0(\omega) = \kappa_2 \Phi_\omega(\omega) - (1-\kappa_2)c - \frac{\kappa_1\kappa_2(1-\kappa_2)(\Phi + c) + (1-\kappa_1)B}{1-\kappa_1\kappa_2}. \tag{34}$$

Divide by ρ to get the equations in the Lemma.

A.3 Proof of Proposition 1

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

Equilibrium conditions 3 and 4 are satisfied by Lemma 1. When all matches are accepted, the distribution of matches is random so that

$$\int_\omega d\Gamma(\omega, h) = g_h(h) M,$$

and

$$\int_h d\Gamma(\omega, h) = g_\omega(\omega)M.$$

Then equations (14) and (15) can be written as

$$\lambda(L - M) = \delta M$$

and

$$\eta(N - M) = \delta M.$$

Clearly λ^* and η^* are the unique solutions to this pair of equations together with equilibrium condition 7.

It remains to be shown that the value functions satisfying equations (3), (5), (4) and (6) exist and are unique. The existence and uniqueness of the wage function follows simply from equation (10).

When all matches are accepted, expected value is simply the average value across all possible partners,

$$E_\omega V(\omega, h) = \int_\omega V(\omega, h) dG_\omega,$$

$$E_h J(\omega, h) = \int_h J(\omega, h) dG_h.$$

Then the HJB equations become simple linear functional equations, and their solutions are given by Lemma 2.

A.4 Proof of Proposition 2

To show (1), we express $V_0(h)$ as

$$V_0(h) = \frac{1}{\rho}\left[\kappa_1 \Phi_h(h) + (1 - \kappa_1)b(h)\right] - \kappa_1 \Omega, \tag{35}$$

where $\Omega = \int_\omega J_0(\omega) dG_\omega(\omega)$ is the expected value of a vacancy. Because $b(h)$ is weakly increasing in h, we just need to show that $\Phi_h(h)$ is increasing. The derivative of the expected output with respect to skill is the same as the expected marginal return to skill, which is always positive. We hence have $V_0'(h) > 0$.

We proceed analogously to prove (2).

Given statement (1) above, both the direct output of a worker-firm match and the outside option of the worker is increasing in h. Because they both positively enter the wage function (10), wages increase in h.

Statements (4) and (5) follow directly from the technology choice equation (1) and random matching. A worker with higher h will chose the import technology for a wider set of ω matches. Given random matching, she is then more likely to be matched with a firm with which she can import together. The same logic applies to productive firms.

To prove Statement (6), first see that within a firm, importers have higher skill (see Figure 5). As Statement (3) predicts, these workers have higher wages.

A.5 Proof of Lemma 3

The solution to the matching problem only depends on δ, ρ, $m()$, N and L. As long as Assumption 1 holds, all matches will be accepted, and the matching rates are given by the same formula.

A.6 Proof of Proposition 3

Statement (1) follows directly from the technology choice equation (1).

To derive statement (2), let us first differentiate $V_0(h)$ with respect to R_F:

$$\frac{\partial V_0(h)}{\partial R_f} = \frac{\kappa_1}{\rho}\left[\frac{\partial \Phi_h(h)}{\partial R_f} - \frac{\kappa_2(1-\kappa_1)}{1-\kappa_1\kappa_2}\frac{\partial \Phi}{\partial R_f}\right].$$

Note that the second term does not depend on h. Differentiating the first term,

$$\frac{\partial \Phi_h(h)}{\partial R_f} = -\int_{\omega^*(h)}^{\bar{\omega}} dG_\omega(\omega) - [A_F F(\omega^*, h) - R_F - A_D F(\omega^*, h) + R_D]\frac{\partial \omega^*}{\partial R_F},$$

but the last term is zero by the definition of ω^*. We then differentiate with respect to h

$$\frac{\partial V_0'(h)}{\partial R_f} = \frac{\kappa_1}{\rho} g_\omega[\omega^*(h)]\frac{\partial \omega^*}{\partial h} \leq 0.$$

We have used the fact that $\omega^*(h)$ is weakly decreasing in h.

To prove (3) and (4), we differentiate the wage function with respect to R_F:

$$\frac{\partial w}{\partial R_F} = -\beta\chi(\omega,h) - (1-\beta)\kappa_1\mu_h(h) + \beta\kappa_2\mu_\omega(\omega) + \frac{\kappa_1\kappa_2[(1-\beta)(1-\kappa_1) - \beta(1-\kappa_2)]}{1-\kappa_1\kappa_2}\mu, \tag{36}$$

with $\mu_h(h) \equiv \int \chi(\omega,h)dG_\omega$ denoting the fraction of type-h workers that are using an imported machine, $\mu_\omega(\omega) \equiv \int \chi(\omega,h)dG_h$ denoting the same fraction for type-ω firms, and μ denoting the overall fraction of importers in the economy.

The first term is the direct effect of cheaper imports. For importers with $\chi(\omega,h) = 1$, the rental of machinery has become cheaper, increasing the surplus of the match. A fraction β of this saving goes to the worker. The second term reflects the change in outside option for the worker. In a new job she will be affected by the reduction in import prices with probability μ_h. The third term reflects the change in outside option for the firm. A new hire will use the imported machine with probability μ_ω. The last term reflects the change in outside option for the average worker vs the average firm and is negative by Assumption 2.

For importers, $\chi(\omega,h) = 1$, which tends to make the derivative negative. Note that the third, positive term is less than β, so that wages depend negatively on R_F. That is, wages of importers increase when R_F decreases. This proves part (3).

For non-importers, $\chi(\omega,h) = 0$, and the sign of the derivative depends on the second through fourth terms. The negative term increases in h, which means that more skilled workers are more likely to gain from trade liberalization. The positive term increases in ω, implying that workers at more productive firms are more likely to lose from trade liberalization. There is a $\omega, \tilde{h}(\omega)$ combination of productivity and skill for which non-importer wages do not change. These are implicitly defined by

$$\beta\kappa_2\mu_\omega(\omega) - (1-\beta)\kappa_1\mu_h(\tilde{h}) = \frac{\kappa_1\kappa_2[\beta(1-\kappa_2) - (1-\beta)(1-\kappa_1)]}{1-\kappa_1\kappa_2}\mu.$$

Because both μ_h and μ_ω are increasing, $\tilde{h}$ is increasing in ω.

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

$$w_{ifot} = \xi \chi_{ifot} + \varepsilon_{ifot}, \tag{37}$$

where χ_{ifot} is the true importer status of a worker i at firm f in occupation o in year t and ε_{ifot} is an orthogonal error term. If we observed χ_{ifot}, we could estimate (37) by simply regressing wages on the importer dummy and would get a consistent estimate of ξ.[30]

However, we only observe

$$\chi_{fot} = \max_i \chi_{ifot}$$

and estimate

$$w_{ifot} = b\chi_{fot} + \varepsilon_{ifot}. \tag{38}$$

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

$$\begin{aligned} \operatorname{plim} \hat{b}_{OLS} &= \mathrm{E}\left(w_{ifot} | \chi_{fot} = 1\right) - \mathrm{E}\left(w_{ifot} | \chi_{fot} = 0\right) \\ &= \xi \Pr(\chi_{ifot} = 1 | \chi_{fot} = 1) < \xi. \end{aligned} \tag{39}$$

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

When we include firm fixed effects in (38), the estimate of b becomes

$$\hat{b}_{FE} = \frac{\sum_{ft} (\bar{w}_{1ft} - \bar{w}_{0ft}) n_{0ft} n_{1ft} / n_{ft}}{\sum_{ft} n_{0ft} n_{1ft} / n_{ft}}, \tag{40}$$

where $\bar{w}_{1ft}$ is the average wage in firm f in year t for workers with $\chi_{fot} = 1$. Similarly, $\bar{w}_{0ft}$ is the average wage for $\chi_{fot} = 0$. 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_{ft}) and the share of observed importers at the firm (n_{1ft}/n_{ft}). Otherwise, the bias in $(\bar{w}_{1ft} - \bar{w}_{0ft})$ is the same.

$$\operatorname{plim} \hat{b}_{FE} = \xi \frac{\sum_{ft} \Pr(\chi_{ifot} = 1 | \chi_{fot} = 1) n_{0ft} n_{1ft} / n_{ft}}{\sum_{ft} n_{0ft} n_{1ft} / n_{ft}} < \xi. \tag{41}$$

[30] In this discussion of measurement error, we simply ignore the issue of endogeneity. We have discussed that at length in Section 4.2.

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

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

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 $1/n_{fot}$ 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 10 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 6.

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 10. 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 $1/n_{fot}$ 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 10 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, as detailed below. 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 7.96 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.[31] This is our measure of generic imports.

[31]Because we only have a sample of workers, firms often import machines for which we observe no suitable operators. For the average firm-year cell, such machines amount to 77.8 percent of the imported machine stock.

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

$$w_{ifot} = \sum_{m=1}^{4} \xi^{(m)} S_{fot}^{(m)} + +\alpha X_{ft} + u_{ifot}. \tag{42}$$

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.

Table 10: Alternative ways of capturing import exposure

	(1) Weighted	(2) No large occupations	(3) $1/N_{fot}$	(4) Intensive margin
Worker exposed to imported machine (dummy)	0.063***	0.046***		
	(0.011)	(0.012)		
Worker exposed to imported machine $\times 1/n_{fot}$			0.031**	
			(0.016)	
Firm is an importer (dummy)	0.006	0.019	0.041**	
	(0.014)	(0.016)	(0.016)	
Specific import per worker (1st quartile)				0.028
				(0.019)
Specific import per worker (2nd quartile)				0.035*
				(0.020)
Specific import per worker (3rd quartile)				0.068***
				(0.022)
Specific import per worker (4th quartile)				0.118***
				(0.023)
Firm is foreign owned (dummy)	0.146***	0.145***	0.132***	0.113***
	(0.015)	(0.017)	(0.017)	(0.018)
Book value of machinery (log)	0.086***	0.086***	0.087***	0.077***
	(0.005)	(0.006)	(0.006)	(0.007)
R^2	0.438	0.486	0.516	0.520
Number of observations	61,173	48,257	61,173	61,173

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.

Column 4 of Table 10 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 7.02 percent, the fourth quartile with 12.55 percent higher wages.

C Appendix C: 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 53 FEOR codes involving the operation of a machine (excluding vehicle drivers). Table 11 provides the full list of occupations used.

There are 290 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 12). Each occupation or product could 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 373 matches.

The average worker is matched with 7.04 machines, and the average machine is matched with 1.29 occupations. The full list of matches is available at https://github.com/korenmiklos/machines-replication/blob/master/table/matches.csv.

D Appendix D: Robustness to occupation matching

To check how the precision of product-occupation matching might affect our results, we have reestimated all worker-level regressions with broader occupation definitions. 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, in this Appendix, we classified all occupations as exposed to imports that are closely related to the machine operator occupation.

Table 13 presents the results on this broader sample, which are both qualitatively and quantiatively similar to our main specification.

Table 11: Machine operator occupations

FEOR code	Description
8111	Food products machine operators
8112	Beverage products machine operators
8113	Tobacco products machine operators
8121	Textile industry machine operators and production line workers
8122	Dressmaking machine operators and production line workers
8123	Leather tanning and processing machine operators and production line workers
8124	Shoemaking machine operators and production line workers
8125	Wood processing machine operators and production line workers
8126	Paper and pulp industry machine operators
8127	Printing machine operators
8131	Petroleum refinery and processing machine operators
8132	Gas making and processing machine operators
8133	Basic chemicals and chemical products machine operators
8134	Pharmaceutical products machine operators
8136	Plastic processing machine operators
8137	Rubber goods manufacturers, vulcanizers
8141	Ceramic products machine operators
8142	Fine ceramics products machine operators
8143	Glass and glass products machine operators
8144	Concrete building block machine operators
8149	Building materials industry machine operators not elsewhere classified
8191	Metallurgical machine operators
8192	Metal working machine operators
8199	Processing machine operators, production line workers not elsewhere classified
8211	Solid minerals extraction machine operators
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
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
8233	Water pump operators
8240	Packaging machine operators
8291	Boiler operators (licensed boilermen)
8292	Decontaminating machine and equipment operators
8293	Agricultural machine operators, mechanics
8299	Other non manufacturing machine operators not elsewhere classified
8311	Agricultural engine drivers and operators
8312	Forestry plant operators
8313	Plant protection machine operators
8319	Agricultural and forestry mobile-plant drivers, operators not elsewhere classified
8321	Earth moving equipment operators
8322	Groundwork machine operators
8323	Road, bridge and railroad building machine operators
8324	Hydromechanical and floating plant operators
8325	Well drilling machine operators
8329	Construction machine operators not elsewhere classified
8341	Crane operators
8342	Elevator and conveying machine operators
8343	Lift trolley operators
8344	Loading/unloading machine operators
8349	Material conveying machine operators not elsewhere classified

Table 12: 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

Table 13: The effect of import exposure on wages—misclassified occupations

	(1) Baseline	(2) Skill controls	(3) Firm controls	(4) IV
Worker exposed to imported machine (dummy)	0.061***	0.048***	0.042***	0.410***
	(0.012)	(0.010)	(0.007)	(0.090)
Firm is an importer (dummy)	0.024*	0.021**		-0.326*
	(0.013)	(0.010)		(0.175)
Firm is foreign owned (dummy)	0.146***	0.113***		0.120***
	(0.015)	(0.012)		(0.023)
Book value of machinery (log)	0.065***	0.048***		0.066***
	(0.009)	(0.007)		(0.010)
R^2	0.477	0.595	0.816	0.418
Number of observations	153,110	153,110	153,110	153,110
Worker controls	Baseline	Baseline+ spline of skill	Baseline+ spline of skill	Baseline
Firm controls	Baseline	Baseline	Firm-year FEs	Baseline
Instruments				Predicted import probability
F-test for 1st stage				62.26

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. Worker controls include indicators for gender and schooling and a quadratic function of worker age. Firm controls include quadratic functions of log employment and firm age. In column 4, worker exposure to imported machine is instrumented with the predicted probability to import for the given occupation and the firm as a whole. Observations are weighted by $1/n_{fot}$, the inverse of the number of workers in a firm-occupation-year cell. 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.