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Abstract

We conduct an empirical investigation into the effects of foreign ownership on worker skills using firm-level data from Spain. To control for endogeneity bias due to selection into foreign ownership, we combine a difference-in-differences approach with a propensity score weighting estimator. Our results provide novel evidence that foreign-acquired firms actively raise the skills of their workforce in response to the acquisition by hiring high-skilled workers and providing worker training. To pin down the mechanism, we exploit unique information on whether firms use their foreign parent in exporting to foreign markets. Our results suggest a fundamental role for market access through the foreign parent in explaining skill upgrading in foreign-acquired firms. We reveal substantial productivity gains within foreign-acquired firms and we show that these gains derive from a concurrent effort to raise worker skills and adopt more advanced technology, suggesting a skill bias in technological innovations. We develop a simple theoretical model of foreign ownership featuring technology-skill complementarities in production that can rationalize our findings.

JEL-Codes: D220, D240, F230, G340.

Keywords: multinational enterprises, mergers and acquisitions, skill-biased technological change, worker training, productivity.

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1 Introduction

A prominent stylized fact in the trade literature is that workers in firms affiliated with foreign multinationals are strikingly different from workers in non-affiliate firms. They stick out as more educated and skilled, as more productive, and as earning higher wages (Heyman et al., 2007; Huttunen, 2007; Hijzen et al., 2013). Where do these differences come from? Two explanations have been proposed. The first is a selection effect, whereby foreign multinationals, instead of acquiring domestic firms at random, target highly productive firms with an exceptional workforce ('cherry-picking') (Almeida, 2007). The second explanation is the existence of a treatment effect of foreign ownership, implying active skill upgrading that would not have occurred had the firm remained in domestic ownership. Since only the second explanation has direct welfare implications for domestic workers, sorting out these scenarios is of central interest to both policymakers and academics.

In this paper, we conduct an in-depth micro-level investigation into the effects of foreign ownership on worker skills. For this purpose, we exploit within-firm variation in ownership structure induced by foreign acquisitions in Spain. To credibly disentangle effects due to treatment versus selection, we combine a difference-in-differences approach with a suitable propensity score reweighting estimator. Our results provide novel evidence that foreign-acquired firms actively raise the skills of their workforce in response to the acquisition. Since we control for 'cherry-picking' in our analysis, our estimates suggest a *causal* interpretation of the effect. While this finding is of obvious policy relevance, identifying the underlying economic mechanism is challenging. There are several views on why foreign-owned firms might raise the skills of their workforce beyond the level of domestically owned firms. One view is that foreign ownership alleviates credit constraints and thus allows firms to move closer to their first-best investment levels (Harrison and McMillan, 2003). Another view is that foreign multinationals transfer superior technology with potentially higher skill requirements to their affiliated firms (Caves, 1996, chapter 7). Previous research has been limited in its ability to sort out these and other possibilities, yet this is crucial for devising and selecting among policy alternatives.

The contribution of our paper is to overcome the limitations of previous research and pinpoint the precise mechanism by which firms respond to foreign acquisitions through skill upgrading. Since we find no evidence for either the credit or the technology transfer channel in our data, we focus on an entirely different mechanism, viz. the role of market access through the foreign parent. Our premise is that firms are able to tap into a larger customer base if the foreign parent entertains an international distribution network. This idea finds strong support in our data, which includes information on whether firms use the foreign parent as a distribution channel for their exports, or whether they export through other means.

Our contribution has a theoretical and an empirical component. On the theoretical side, we demonstrate how market access through the foreign parent can explain rising skill levels within foreign-acquired firms. For this purpose, we develop a model of monopolistic competition in which firms can adjust skills via two margins: first, the composition of the workforce regarding high- and low-skilled labor; and second, the provision of worker training augmenting the productivity of all workers regardless of skill type. Motivated by the evidence from a number of carefully executed empirical studies, we assume that both margins are subject to a complementary relationship with the (endogenous) technology level of the firm.[1] Our model shows how an increase in market size due to a change in ownership from domestic to foreign creates incentives for firms, not only to innovate, but also to raise the level of worker training and the share of high-skilled workers in the firm.

To validate our model empirically, we use Spanish firm-level data from the Encuesta Sobre Estrategias Empresariales (ESEE) for the period 1998-2013.[2] This data-set is exceptionally well suited for our analysis due to its breadth and level of detail.[3] It collects information, not only about the ownership structure of firms or the means by which they access foreign markets, but also about various dimensions of skills, such as the workforce composition regarding education, the training of workers in various different fields, as well as the hiring of recent university graduates. In addition, it includes information on innovation activities, technology imports, and the financial situation of firms. The richness of our data enables us to provide substantive evidence supporting the central mechanism of our model—market access through the foreign parent coupled with technology-skill complementarities in production—in explaining skill upgrading in foreign-acquired firms. At the same time, it allows us to minimize plausible alternative explanations for skill upgrading, viz. the relaxation of credit constraints following acquisition or technology transfers from the foreign parent to the domestic affiliate.

Specifically, we generate three sets of empirical results that provide considerable support for our theoretical model. First, we present robust evidence for skill upgrading caused by foreign acquisitions. Skill upgrading comes in two forms: first, an increase in the share of high-skilled workers due to a shift in the hiring policy towards fresh university graduates; and second, an increase in worker training, not just overall, but also specifically in those fields that are closely related to the production technology of the firm (engineering and IT). In line with our model, both forms of skill upgrading occur simultaneously with the adoption of higher levels of technology following acquisition. Moreover, while skill upgrading is present in *foreign* acquisitions, we show that this is not the case in *domestic* acquisitions. This is consistent with the idea that the cross-border dimension of the acquisition is crucial in facilitating access to foreign markets, and thus in understanding skill upgrading on the part of the acquired firm.

Secondly, we inquire into the exact mechanism behind these results, and demonstrate that

[1]The literature has documented a positive link between the demand for skill and different types of innovation activities. For instance, Akerman et al. (2015) provide evidence that technological change in the form of broadband adoption increases the marginal productivity of skilled workers. Levy and Murnane (1996) and Autor et al. (2003) document a positive link between computers and skill demand. Lewis (2011) shows that investments in automation machinery substituted for the least skilled workers and complements more skilled workers. Empirical evidence on the complementarity between technology upgrading and worker training can be found in Ichniowski et al. (2007) who show that operating new IT-enhanced capital equipment increases the need for technical and problem-solving skills which firms meet by adopting new human resource practices (e.g. worker training).

[2]The country and period are particularly interesting for our analysis because the Spanish economy received sizable inflows of FDI during our sample period. While the stock of inward FDI remained relatively stable at around 10-20% of GDP during the 1990s, it increased to almost 50% during the 2000s (UNCTAD FDI database).

[3]Among others, it has been used in various different contexts by Antràs (2015), Delgado et al. (2002), Garicano and Steinwender (2016), and Kohler and Smolka (2014).

market access through the foreign parent clearly dominates other plausible channels. Since our data identify precisely which firms rely on their foreign parent in gaining access to foreign markets, we can use this information to discriminate within the group of foreign-acquired firms. As it turns out, skill upgrading (whether through hiring or training) is found just for those firms that use their foreign parent for exporting, but not for other firms. To further strengthen these results and rule out both the credit and the technology transfer channel, we show that there are no changes in key financial figures (debt share, debt maturity, and debt service ratio) following acquisition, and that skill investments respond, neither to the financial situation of firms, nor to whether or not they import technology from abroad.

Finally, we investigate potential complementarities between technology and skills in the production process. We first show that firm output increases by more than 10% one year after the acquisition. We then proceed by showing that the variety of actions taken by the firm in response to the acquisition—innovation, hiring of high-skilled workers, and worker training—explain most, if not all, of this increase. In addition, we show that innovation *interacts* with both forms of skill upgrading. This finding underpins the technology-skill complementarities assumed in our model and supports the notion that technological progress that occurs in relation to foreign acquisitions is—at least in the case of Spain and for the period we investigate—skill biased.

Our paper contributes to several strands of the literature. First, it contributes to the literature on the nexus between foreign direct investment (FDI) and the relative demand for skilled labor. Influential empirical studies at the industry level are Blonigen and Slaughter (2001), Fabbri et al. (2003), and Taylor and Driffield (2005), while more recent papers studying the effects of foreign ownership use firm-level data, e.g. Almeida (2007) and Hijzen et al. (2013). This literature, in our view, has produced somewhat mixed evidence. Our contribution is to lay bare, both theoretically and empirically, one important channel by which FDI in the form of foreign acquisitions leads to skill upgrading.[4] Moreover, the use of rich survey data allows us to study within-firm adjustments, not just in the share of high-skilled workers, but also in the provision of worker training. This potentially important dimension of skill upgrading has largely escaped the attention of other studies in this literature.

Secondly, our paper contributes to an active literature that tries to, not only identify the causal effect of foreign ownership on firm performance, but also pinpoint why exactly foreign-acquired firms are often found to perform better than firms remaining in domestic ownership. An important example is Guadalupe et al. (2012), who use the same Spanish firm-level data as we do and who emphasize the market size effect of foreign ownership in boosting innovation and productivity following acquisition.[5] We contribute to this literature by focusing on (different forms of) skill up-

[4] There is a different literature supporting the idea that an increase in market size due to 'globalization' leads firms to engage in skill upgrading (Yeaple, 2005) or technology upgrading (Lileeva and Trefler, 2010; Bustos, 2011). However, these papers focus on trade liberalization as the reason why some firms now face a higher demand for their output, and so they are silent about the effects of foreign acquisitions, which is the focus of our paper.

[5] Another important example is Arnold and Javorcik (2009), who show that foreign-acquired plants in Indonesia experienced substantial restructuring upon acquisition involving a steep increase in machinery investment and subsequent productivity gains.

grading within firms, and by emphasizing interactions between technology and skills that have not received much attention in the literature, but which we show to be crucial for understanding post-acquisition performance. The empirical evidence we present, along with the theoretical model we propose, demonstrates that the productivity gains within foreign-acquired firms derive from combining new and superior technology with suitably trained workers as well as a higher skill intensity in production. This is in sharp contrast to Guadalupe et al. (2012), who attribute all changes in post-acquisition performance to changes in technology.

Finally, by providing evidence on the relationship among foreign ownership, technology, and skills, our paper contributes to the influential and extensive literature on skill-biased technological change. Excellent reviews of this literature can be found in Acemoglu (2003), Bond and Van Reenen (2007), and Goldin and Katz (2007). One potential limitation in this literature is that skill-biased technological change is difficult to observe directly, and so the evidence usually derives from aggregate data, i.e., industry- or country-level data. This ignores substantial within-industry variation across firms as well as endogeneity in technology and skill choices at the firm level (see Bøler, 2015). More recent studies use exogenous variation in the availability of new technology—e.g. broadband internet as in Akerman et al. (2015)—to test whether and to what extent technological change is skill biased. By exploiting within-firm variation in technology and skills triggered by changes in ownership structure from domestic to foreign, we provide a novel and tangible piece of evidence, at the firm level, that supports the notion that technological progress is skill biased.

The remainder of our paper proceeds as follows. In Section 2 we develop a simple model of foreign ownership featuring an environment of monopolistic competition and technology-skill complementarities in production. In Section 3 we describe our data-set and the sample we use. In Section 4 we present our empirical analysis and the main findings. Section 5 concludes.

2 Model

Consider an industry in which firms produce differentiated varieties and sell their output in a monopolistically competitive market. Firms face an iso-elastic demand function of the form

$$q(v) = A_m p(v)^{-\sigma}, \tag{1}$$

where $q(v)$ and $p(v)$ denote demand and price for variety v, respectively, $\sigma > 1$ measures the (constant) elasticity of substitution between any two varieties, and A_m is a measure of market size with $m \in (d, f)$.[6] The key difference between firms in foreign ownership ($m = f$) versus domestic ownership ($m = d$) is that foreign-owned firms can serve additional customers through the international distribution network of the foreign parent. To formalize this idea in the simplest

[6] Maximizing a constant-elasticity-of-substitution (CES) utility function of the form $U = \left[\int_{v\in V} q(v)^{\frac{\sigma-1}{\sigma}} dv\right]^{\frac{\sigma}{\sigma-1}}$ subject to a consumer's budget constraint $E = \int_{v\in V} p(v)q(v)dv$, where E are total expenditures on the set of available varieties V, gives the demand function in Eq. (1) with $A \equiv EP^{\sigma-1}$ and $P = \left[\int_{v\in V} p(v)^{1-\sigma} dv\right]^{\frac{1}{1-\sigma}}$ denoting the price index.

possible way, we assume that foreign-acquired firms gain access to an additional market abroad denoted by A^*, so that $A_f = A_d + A^*$ with $A_f > A_d$.[7]

Production of a specific variety v requires the performance of a continuum of tasks (for convenience normalized to the unit interval). Similarly to Acemoglu and Autor (2011), we use a simple Cobb-Douglas production function to formalize the assembly of tasks in the production of variety v:

$$x(v) = \phi(v) \exp \left[\int_0^1 \ln x(v,i) di \right], \tag{2}$$

where $\phi(v)$ is an (exogenous) productivity parameter and $x(v,i)$ is the production level of task i in firm v producing total firm output $x(v)$.

To highlight the link between foreign ownership, innovation, and skill upgrading, we assume that output at the task level, $x(v,i)$, depends on the task, the skill, and the technology. More specifically, we assume that tasks can be ordered according to their complexity where a higher index i reflects higher complexity. High-skilled workers have a productivity advantage in the performance of complex tasks, i.e., we assume a complementarity between the complexity of a task and the skill of a worker when determining labor productivity at the firm-task level (similar to Acemoglu and Autor, 2011). Moreover, the productivity advantage of high-skilled workers is increasing in the level of technology. Thus, high-skilled workers have a comparative advantage over their low-skilled coworkers in using modern, more advanced technology. Finally, firms can raise the productivity of their workers, regardless of their skill type, by training them in performing tasks more efficiently. As will become evident below, we assume a complementarity between worker training and technology, generating incentives for firms to provide worker training whenever they adopt new and more advanced technology.[8]

We omit variety index v from now on and assume that task output is determined according to the following linear homogeneous production function:

$$x(i) = \beta(\lambda, \tau) \left[l(i) + \alpha(\lambda, i) h(i) \right], \tag{3}$$

where $l(i)$ and $h(i)$ denote the quantities of low- and high-skilled labor, respectively, and $\alpha(\lambda, i)$ captures the productivity advantage of high-skilled workers in the production of task i as a function of the firm's technology level λ. The function $\beta(\lambda, \tau)$, on the other hand, is an overall productivity shifter which applies equally to both high- and low-skilled labor, and which depends, not only on the firm's technology level λ, but also on the level of worker training τ.[9]

[7] While this way of modelling the market size effect of foreign ownership is admittedly simple, it gives rise to positive selection into foreign ownership as found in our data (as will become evident below). In addition, it leaves open the possibility that A_d includes both domestic and foreign markets. Adopting a slightly more sophisticated modelling strategy featuring productivity-dependent selection into different sets of markets due to market-specific fixed costs is straightforward and leaves all our results unchanged.

[8] Koch (2016) presents a related but more restrictive framework in which firms endogenously assign high- and low-skilled workers to tasks that differ in their complexity, but without considering endogenous investments in innovation and training, as we do here. In contrast to our model, the model in Koch (2016) allows studying how trade liberalization leads to skill adjustments within firms through a general equilibrium effect.

[9] The firm's productivity parameter $\phi(v)$ and the productivity shifter $\beta(\lambda, \tau)$ are isomorphic in governing a firm's

To capture the complementarity and the link between task-specific complexity and technology choice, we impose that $\alpha(\lambda, i)$ is a twice differentiable, strictly increasing and convex function of i, and that it is strictly increasing in the technology level λ. For concreteness, and to ensure that the analysis remains tractable, we set $\alpha(\lambda, i) = \exp[\lambda i]$ for all $i \in [0, 1]$. This implies that a high-skilled worker assigned to the least complex task is as productive as her low-skilled coworker, whatever the technology level, since her specific skills are not required for performing the respective task. Things are different in the case of a more complex task, where the higher skill level generates an absolute productivity advantage that is increasing in the technology level of the firm. Importantly, new technology (captured by a rise in λ) will disproportionately favor more complex tasks, in the sense that the productivity advantage of high-skilled labor will increase more strongly the more complex the task is.

Finally, to formalize the complementarity between the level of technology and worker training, we set $\beta(\lambda, \tau) = \lambda\tau$ and assume that $\lambda \geq 1$ and $\tau \geq 1$. This implies that a change in technology giving rise to a higher value of λ will magnify the productivity gains arising from worker training.

2.1 Firms' optimization problem

After entering the industry and learning about the (exogenous) firm productivity ϕ, firms maximize their profits according to a four-stage optimization problem.[10] In the first step, firms choose the optimal level of technology, comparing the productivity gains due to a higher λ with the costs of innovation $C(\lambda) = \lambda^{\epsilon_0}$. In the second step, firms decide upon the optimal level of worker training, comparing the associated productivity gains with the costs of training $C(\tau) = \tau^{\epsilon_1}$. In the third step, firms determine the optimal allocation of skills to tasks and, thus, the range of tasks performed by low- and high-skilled workers, respectively, by comparing the productivity advantage of high-skilled workers with the skill premium $\omega \equiv w_h/w_l$ (where $w_j, j = l, h$ are the costs of one unit of labor of type j). In the fourth and final step, firms choose output at the task level, which is equivalent to determining the task-level employment for a given skill assignment and a given technology and training choice. We solve the model by backward induction.

2.1.1 Optimal employment at the task level – stage 4

For a given choice of technology and training and a given assignment of workers to tasks, firms set task-level output $x(i)$ to maximize their profits

$$\pi = px - \int_0^1 x(i)c_k(i)di - C(\lambda) - C(\tau) - f, \tag{4}$$

subject to (1) and (2). In this equation, $c_k(i)$ denotes the unit costs of a firm performing task i with the preassigned skill type $k = l, h$, and f denotes fixed costs required to manage the firm, organize

overall performance. However, while $\phi(v)$ is exogenous from a firm's perspective, $\beta(\lambda, \tau)$ responds to endogenous firm adjustments in the levels of technology (λ) and training (τ) (see below).

[10] Notice that the firm's profits will be maximized regardless of whether the owner of the firm is located in the domestic or the foreign economy.

the production process, set up a production plant, and so on.[11] Due to the technology in Eq. (2) being of the Cobb-Douglas type and the special case of each task entering the production function symmetrically, cost shares are the same for all tasks. To be more specific, substitution of (1) into the first-order condition $\partial\pi/\partial x(i) = 0$ gives

$$\frac{\sigma - 1}{\sigma} px = x(i)c_k(i) \quad \forall i \in [0, 1]. \tag{5}$$

A direct implication of the identical cost shares is that the firm employs the same number of workers of a given skill type in all tasks performed by workers of this skill type, i.e., $w_l l(i) = w_l l$ and/or $w_h h(i) = w_h h$.

2.1.2 Optimal skill intensity – stage 3

With the optimal amount of workers for each task i at hand we can proceed and determine the optimal range of tasks that are performed by the two skill types. Ordering tasks according to their complexity allows us to define a unique threshold task $z \in (0, 1)$ where the firm is indifferent between hiring low-skilled or high-skilled workers (given relative wages $\omega = w_h/w_l$). In other words, the unit costs of performing task z are the same irrespective of the assigned skill type $k = l, h$, which implies $c_l(z) = c_h(z)$ or, equivalently, $\omega = \exp[\lambda z]$ and hence

$$z(\lambda) = \frac{\ln \omega}{\lambda}. \tag{6}$$

Due to the relative advantage of high-skilled workers in performing more complex tasks, it follows that low-skilled workers will be assigned to all tasks $i < z(\lambda)$, while high-skilled workers will be assigned to all tasks $i \geq z(\lambda)$.[12] Having solved the firm's assignment problem, we are now able to compute a firm's skill intensity, which we denote by $s(\lambda)$. We define $L = \int_0^{z(\lambda)} l(i)di = z(\lambda)l$ and $H = \int_{z(\lambda)}^1 h(i)di = [1 - z(\lambda)]h$ as a firm's total low-skilled and high-skilled variable labor input, respectively, and note that $w_l l(i) = w_l l$ and $w_h h(i) = w_h h$ from above, so that a firm's skill intensity is given by

$$s(\lambda) \equiv \frac{H}{L} = \frac{1 - z(\lambda)}{z(\lambda)\exp[\lambda z(\lambda)]} \overset{(6)}{=} \frac{1 - z(\lambda)}{z(\lambda)\omega}. \tag{7}$$

From inspection of (6) and (7) one can immediately see that technology upgrading, captured by an increase in λ, leads to an increase in a firm's skill intensity $s(\lambda)$. A higher level of technology increases the comparative advantage of high-skilled workers in the performance of complex tasks and firms respond to this by hiring high-skilled workers and assigning them to a broader range of

[11] As we do not solve the model in general equilibrium, we keep the analysis as simple as possible and do not specify in which units the costs of technology, the costs of worker training and the fixed costs are paid (in units of low-skilled labor, high-skilled labor or any numéraire good). The results of the model remain unaffected as long as the unit costs are not firm specific.

[12] Since $z(\lambda)$ is restricted to values between zero and one, we allow λ to vary within the interval $[\ln \omega, \infty)$.

tasks (so that $z(\lambda)$ decreases).[13]

Having determined the threshold task z we can combine Eqs. (2) and (3) to rewrite firm output as

$$x = \phi\varphi(z,\lambda,\tau)\exp\left[\int_0^{z(\lambda)} \ln l(i)di + \int_{z(\lambda)}^1 \ln h(i)di\right] \tag{8}$$

where $\varphi(z,\lambda,\tau)$ is defined as

$$\varphi(z,\lambda,\tau) \equiv \exp\left[\int_0^1 \ln\beta(\lambda,\tau)di + \int_{z(\lambda)}^1 \ln\alpha(\lambda,i)di\right] = \lambda\tau\exp\left[\lambda\frac{1-z(\lambda)^2}{2}\right]. \tag{9}$$

According to (8), firm productivity consists of two parts: an exogenous baseline productivity ϕ and an endogenous productivity term $\varphi(z,\lambda,\tau)$ which varies with the technology choice, the implied assignment of skills to tasks, and the level of worker training. From $\varphi_\lambda > 0$, $\varphi_\tau > 0$, and $z_\lambda < 0$ it follows that firms can raise their productivity through investments in technology and worker training, as well as through the assignment of a larger range of tasks to high-skilled workers. More specifically, productivity gains can arise from an increase in λ, and they are clearly stronger if firms additionally provide worker training ($\varphi_{\lambda\tau} > 0$) and hire new high-skilled workers by reducing $z(\lambda)$. However, upgrading the firm's technology, providing more worker training, and producing with a higher skill intensity raises the costs of a firm and therefore involves a trade-off. How the profit-maximizing levels of worker training and technology are determined is now discussed in the solution to stages 2 and 1.

2.1.3 Optimal level of worker training – stage 2

To derive the optimal level of worker training, we first compute the optimal price set by a firm:[14]

$$p = \frac{\sigma}{\sigma-1}\frac{w_l^{z(\lambda)}w_h^{1-z(\lambda)}}{\phi\varphi(z,\lambda,\tau)} \overset{(6)}{=} \frac{\sigma}{\sigma-1}\frac{w_h}{\phi\tau\widetilde{\lambda}}, \tag{10}$$

[13] The positive link between innovation and a firm's skill intensity is, of course, a direct implication of our assumption that the productivity advantage of high-skilled workers is increasing in λ. Alternatively we could use a more general functional form for $\alpha(\lambda,i)$, e.g. $\alpha(\lambda,i) = \exp[\lambda^\kappa i]$, where the parameter κ determines the sign of the relation between innovation and the productivity advantage of high-skilled workers. If $\kappa < 0$ (> 0), innovation reduces (increases) the comparative advantage of high-skilled workers, and firms will respond by lowering (raising) their skill intensity. If $\kappa = 0$, innovation is skill neutral and does not affect the optimal allocation of skills to tasks. We decided against the more general functional form as several studies have documented the advantage of high-skilled workers in using more advanced technology (see the literature review in footnote 1). Moreover, our empirical analysis below demonstrates that foreign-acquired firms increase their skill intensity upon acquisition, in line with the parameterization we use in the text.

[14] We first integrate (5) over the unit interval, which shows that prices are set as a constant markup over variable unit costs: $p = [\sigma C]/[(\sigma-1)x]$, where $C \equiv \int_0^1 x(i)c_k(i)di$ are a firm's total variable labor costs. Using Eq. (7) we can rewrite a firm's total variable labor costs as $C = [w_l L/H + w_h]H = w_h h$ and this firm's output as $x = \phi\varphi(\cdot)\{[(1-z(\lambda))/z(\lambda)]L/H\}^{z(\lambda)}h = \phi\varphi(\cdot)\omega^{z(\lambda)}h$. Hence, the variable unit costs of this firm are given by $C/x = w_l^{z(\lambda)}w_h^{1-z(\lambda)}/[\phi\varphi(\cdot)]$, which is equal to the marginal costs of the respective producer. Constant markup pricing therefore gives (10).

where

$$\widetilde{\lambda} \equiv \lambda \omega^{z(\lambda)} \exp\left[\lambda \frac{1-(\ln \omega/\lambda)^2}{2}\right] = \lambda \exp\left[\frac{1}{2}\lambda + \frac{(\ln \omega)^2}{2\lambda}\right]. \tag{11}$$

Noting that firm revenues r are given by $r = px$ and accounting for (1) and (10), we can write profits as

$$\pi = \frac{A_m}{\sigma}\left[\frac{\sigma}{\sigma-1}\frac{w_h}{\phi\tau\widetilde{\lambda}}\right]^{1-\sigma} - \lambda^{\epsilon_0} - \tau^{\epsilon_1} - f. \tag{12}$$

Maximizing profits with respect to training expenditures, setting the respective equation equal to zero and solving for τ, we can compute

$$\tau = \left\{\frac{\sigma-1}{\sigma}\frac{A_m}{\epsilon_1}\left[\frac{\sigma-1}{\sigma}\frac{\phi\widetilde{\lambda}}{w_h}\right]^{\sigma-1}\right\}^{\frac{1}{\epsilon_1-\sigma+1}}. \tag{13}$$

Eq. (13) determines the optimal level of worker training as a function of initial productivity ϕ, market size A_m, technology level λ, and other model parameters. Provided that training costs are sufficiently convex, such that $\epsilon_1 > \sigma - 1$, we have $\tau_\phi > 0$ and $\tau_{A_m} > 0$, i.e., firms with higher initial productivity and access to more markets provide more training. Furthermore, we have $\widetilde{\lambda}_\lambda > 0$ and thus $\tau_\lambda > 0$. Hence, producing with a more advanced technology will prompt the firm to raise investment in worker training.

2.1.4 Optimal level of technology – stage 1

Substituting the optimal level of worker training in Eq. (13) into the profit function, we can rewrite profits solely as a function of the level of technology and exogenous model parameters:

$$\pi = \frac{\epsilon_1-\sigma+1}{\sigma-1}\left[\frac{\sigma-1}{\sigma}\frac{A_m}{\epsilon_1}\right]^{\frac{\epsilon_1}{\epsilon_1-\sigma+1}}\left[\frac{\sigma-1}{\sigma}\frac{\phi}{w_h}\right]^{\frac{\epsilon_1(\sigma-1)}{\epsilon_1-\sigma+1}}\widetilde{\lambda}^{\frac{\epsilon_1(\sigma-1)}{\epsilon_1-\sigma+1}} - \lambda^{\epsilon_0} - f. \tag{14}$$

Maximizing profits in Eq. (14) with respect to λ and setting the respective equation equal to zero gives:

$$\left[\frac{\sigma-1}{\sigma}\frac{A_m}{\epsilon_1}\right]^{\frac{\epsilon_1}{\epsilon_1-\sigma+1}}\left[\frac{\sigma-1}{\sigma}\frac{\phi}{w_h}\right]^{\frac{\epsilon_1(\sigma-1)}{\epsilon_1-\sigma+1}}\widetilde{\lambda}^{\frac{\epsilon_1(\sigma-1)}{\epsilon_1-\sigma+1}}\left[\frac{1}{\lambda}+\frac{1}{2}-\frac{1}{2}\left(\frac{\ln\omega}{\lambda}\right)^2\right] = \epsilon_0\lambda^{\epsilon_0-1}. \tag{15}$$

Provided that the costs of innovation are sufficiently convex, π_λ in Eq. (15) implicitly determines the optimal level of technology as a function of initial productivity, market size, and other model parameters.[15] Using the implicit function theorem, we can compute $d\lambda/d\phi = -\pi_{\lambda\phi}/\pi_{\lambda\lambda} > 0$. Hence, larger and more productive firms will produce with a higher technology level compared to their less productive competitors within the same industry.

2.2 Impact of foreign ownership

Having solved a firm's four-stage optimization problem, we are now equipped to discuss how foreign ownership affects the relevant choice variables of the firm. Specifically, the new owner compares the potential profit income before and after the acquisition and decides upon the optimal level of technology, the optimal level of worker training, as well as the optimal skill intensity of the firm. Importantly, the change from domestic to foreign ownership can influence the technology and training decisions directly through a market size effect, i.e., an increase in A_m due to an additional export destination becoming available through the foreign parent. In particular, there will be a positive effect on the investment decisions of the acquired firm according to Eq. (15) and $d\lambda/dA_m = -\pi_{\lambda A_m}/\pi_{\lambda\lambda} > 0$ since larger revenues from serving additional foreign consumers raises the incentives to innovate. From inspection of Eq. (13) we can see that firms will also increase their training expenditures due to a direct market size effect, $\tau_{A_m} > 0$, as well as the complementarity between training and technology, $\tau_\lambda > 0$. In addition, firms will hire high-skilled workers and assign them to a broader range of tasks according to Eq. (6).

The complementarity between technology upgrading and skill upgrading along with the respective productivity gains are illustrated in Figure 1. The left panel of Figure 1 illustrates productivity gains due to changes in the productivity advantage schedule $\alpha(\cdot)$ for high-skilled workers (keeping training expenditures constant), while the right panel illustrates productivity gains arising from technology upgrading and increased worker training (keeping the productivity advantage of high-skilled workers and, thus, z constant). For a given technology and optimal skill intensity the realized productivity advantage of high-skilled workers is captured by area A in the left panel of Figure 1. New investments in technology lead to an increase in λ (to λ') and thus rotate the productivity advantage curve for high-skilled workers counter-clockwise in task 0. For a given share of tasks performed by high-skilled workers, i.e., for a given z, the productivity gains of high-skilled workers due to better technology are captured by area B. However, as the productivity advantage of high-skilled workers also increases in tasks that are less complex than the threshold task, firms will increase their skill intensity by reducing z (to z') and thus realize productivity gains captured by area C. Moreover, the new technology has a direct positive impact on the efficiency of all workers and raises—due to a complementarity effect—the incentives for firms to invest in worker training. These productivity gains are captured in the right panel of Figure 1, where the areas D and E depict the productivity gains from innovation and worker training, respectively.

[15]To see this we can compute $\pi_{\lambda\lambda} = B\widetilde{\lambda}^{\frac{\epsilon_1(\sigma-1)}{\epsilon_1-\sigma+1}} \left\{\frac{\epsilon_1(\sigma-1)}{\epsilon_1-\sigma+1}[2\lambda + \lambda^2 - (\ln\omega)^2]^2 + 4\lambda[(\ln\omega)^2 - \lambda]\right\} - 4\epsilon_0(1+\epsilon_0)\lambda^{\epsilon_0+2}$, with $B \equiv \epsilon_1 \left[\frac{\sigma-1}{\sigma}\frac{A_m}{\epsilon_1}\right]^{\frac{\epsilon_1}{\epsilon_1-\sigma+1}} \left[\frac{\sigma-1}{\sigma}\frac{\phi}{w_h}\right]^{\frac{\epsilon_1(\sigma-1)}{\epsilon_1-\sigma+1}}$. Hence, if ϵ_0 is sufficiently large (relative to all other model parameters), the costs of innovation (right hand side of Eq. (15)) are increasing faster then the respective revenue gains (left hand

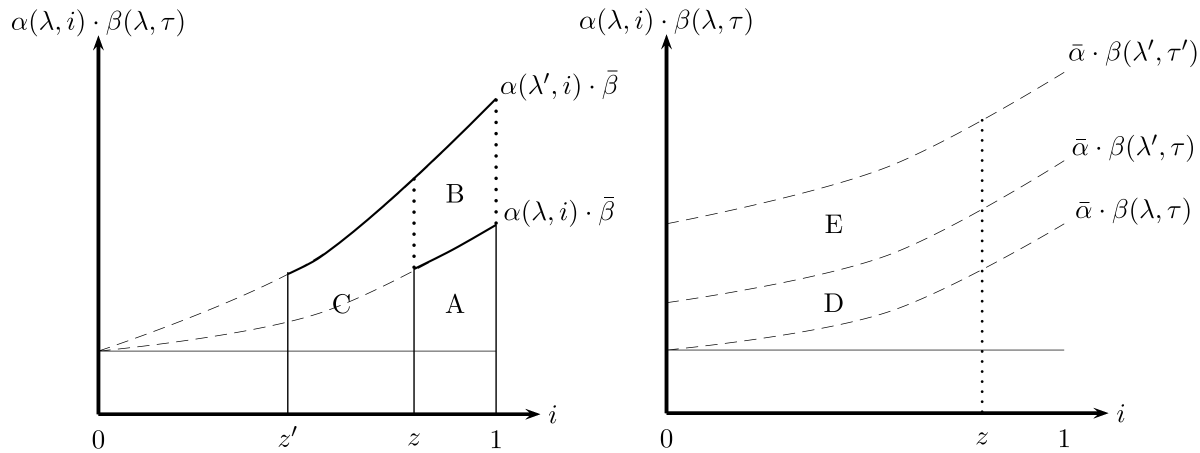

Figure 1: Productivity gains - innovation, skill intensity, and worker training

Taking stock, the model predicts that firms will upgrade their production technology and train their workers following acquisition. Moreover, they will raise the share of high-skilled workers in production and assign them to a broader range of tasks. All these actions will generate productivity gains within firms. One thing to note is that these theoretical predictions can be generated, not just by foreign acquisitions, but by any demand shifter. In our model, the foreign-acquired firm's market size expands from A_d to A_f due to an additional export destination becoming available through the foreign parent. Other shocks can generate similar expansions in market size and thus likewise trigger adjustments in firms' skill and technology choices. The significance of this mechanism has been validated empirically in different contexts. For example, Bustos (2011) demonstrates that exporters from Argentina adopted higher levels of technology following an increase in market size caused by the introduction of a regional free trade agreement. Lileeva and Trefler (2010) also find that improved foreign market access due to the elimination of U.S. tariffs prompted Canadian plants to innovate more and adopt more advanced technologies. Bas (2012) provides evidence from Chile on the relationship between international trade, technology choice, and skill upgrading. One important aspect that sets foreign acquisitions apart from tariff reductions (as well as many other shocks affecting market size) is that they are endogenous to initial firm productivity. This poses an important challenge in the empirical analysis, and we will come back to this point below. Another aspect is that foreign acquisitions are often associated with other adjustments within firms that are orthogonal to the market size channel, yet may also induce firms to upgrade skills and technology. For example, it could be that the foreign parent provides worker training at an internal price that is lower than the market rate, such that the cost (shape) parameter ϵ_1 is lower for foreign-owned than for domestically owned firms. In a similar vein, the foreign parent may provide access to better or less expensive technology, which can be captured by a decrease in ϵ_0 and thus lower marginal costs of innovation. Yet another possibility that we mention in the introduction is that foreign ownership provides firms with better access to finance, either through the internal capital

side of Eq. (15)) and thus $\pi_{\lambda\lambda} < 0$.

market of the multinational firm, or through better access to foreign capital markets (or both). It is straightforward to spell out these ideas in detail within our theoretical model. However, since we are able to pinpoint empirically the market size effect as the driving force behind the adjustments taking place within foreign-acquired firms, our theoretical model abstracts from these alternative possibilities and focuses exclusively on the implications of improved foreign market access.

We conclude this section with a brief remark on the acquisition decision of foreign multinationals.[16] Here we want to emphasize that acquisitions are not random. To see this, we can use Eq. (12) to compute the surplus generated by the acquisition as:

$$\pi^* - \pi = \frac{1}{\sigma}\left(\frac{\sigma}{\sigma-1}\frac{w_h}{\phi}\right)^{1-\sigma}\left[A_f\left(\tau^*\widetilde{\lambda}^*\right)^{\sigma-1} - A_d\left(\tau\widetilde{\lambda}\right)^{\sigma-1}\right] - \Delta_{C(\lambda)} - \Delta_{C(\tau)} \geq 0, \tag{16}$$

where we use an asterisk $*$ to denote variables *after* the acquisition, and Δ to denote cost differentials due to changes in innovation λ and training τ, respectively. As can be shown based on (16) along with our findings regarding endogenous skill and technology choices made by acquired firms, a given increase in market size generates a larger surplus in firms with a higher initial productivity level ϕ.[17] This reflects complementarities among market size, technology upgrading, skill upgrading, and initial firm productivity and implies that foreign multinationals have an incentive to acquire the more productive domestic firms and do 'cherry-picking'. We find clear evidence supporting this implication of our model in our Spanish firm-level data.[18] These theoretical and empirical results highlight the need to control for selection when estimating the effect of foreign ownership on the level of worker skills, as we do later on.

3 Data

The data we use in our empirical analysis come from the Encuesta Sobre Estrategias Empresariales (ESEE) provided by the SEPI foundation in Madrid. The ESEE is an annual survey covering roughly 1,900 Spanish manufacturing firms each year and collecting unusually rich information on strategic firm decisions along with key items of firms' balance sheets as well as profit and loss statements. What makes the ESEE data especially interesting for our analysis is that it records, not only the ownership structure of the firm (foreign vs. domestic), but also specific actions taken by the firm aimed at upgrading the skills of its workforce, as well as information on market access,

[16] This decision can be modelled by analogy to Guadalupe et al. (2012), assuming competition among foreign multinationals in the acquisition market, a fixed acquisition cost, and an endogenous split of the surplus generated by the acquisition between buyer and seller. We refer the interested reader to Guadalupe et al. (2012, p. 3601f.) for details.

[17] This can be seen from $\frac{d(\pi^*-\pi)}{d\phi^{\sigma-1}} = \frac{1}{\sigma}\left(\frac{w_h\sigma}{\sigma-1}\right)^{1-\sigma}\left[A_f\left(\tau^*\tilde{\lambda}^*\right)^{\sigma-1} - A_d\left(\tau\tilde{\lambda}\right)^{\sigma-1}\right] > 0$ according to our assumption that $A_f > A_d$.

[18] Since the acquisition decision is not the focus of our analysis, we relegate detailed empirical results to Appendix A.2. We should also like to point out that, while heterogeneity in initial firm productivity generates positive selection as found in our data, it is not crucial for the effects of foreign ownership on skill upgrading that we reveal later on in our empirical analysis. Neary (2007), Nocke and Yeaple (2007), and more recently Brakman et al. (2018) analyze the acquisition decision in general equilibrium frameworks.

finances, innovation, technology imports, etc. In the following we provide details on the specific information we exploit in our analysis.

First of all, the ESEE data-set provides direct firm-level information on the workforce composition by education (Master's degree; Bachelor's degree; no university degree), on the hiring of recent university graduates, and on worker training in various categories (training in engineering; IT; language; marketing; and other). This allows us to study different margins of skill upgrading, viz. a shift in the hiring policy towards fresh university graduates with a corresponding increase in the skill intensity of the firm, as well as an increase in the training workers receive while employed. Secondly, we exploit explicit and unique information on how firms access foreign markets, as the survey asks firms whether they use the foreign parent as a distribution channel for their exports, or whether they export through other channels (through their own means; through domestic specialized intermediate agents; or through cooperative export agreements with other firms). Thirdly, the data include direct information on firms' innovation activities and thus technology upgrading. We focus on process innovation (new machines; new methods of organizing production; both new machines and new methods) and the assimilation of foreign technologies, since these activities directly target the production efficiency of the firm. The variables we use are dummy variables indicating whether the firm carried out the respective activity in a given year. Fourthly, the data allow painting a comprehensive picture of firms' financial situation using firms' debt share (total debt over total assets), debt maturity (share of short-term debt in total debt), and debt service ratio (sum of debt and interest payments over total sales). Finally, we are able to compute relatively precise measures of output and productivity. Output is defined as the value of goods production expressed in constant 2006 prices. In contrast to most other data-sets, our data include firm-level information on price changes over time. Hence, changes in our output measure over time within a firm reflect changes in physical output, rather than changes in prices (which could be driven by an increase in markups within foreign-acquired firms). Labor productivity, which we use to control for selection into foreign ownership, is defined as real value added per effective working hour.

The sample we use is an unbalanced panel of more than 3,300 different firms over the period 1998-2013. The initial sampling of the data in 1990 (the first year of the survey) had a two-tier structure, combining exhaustive sampling of firms with more than 200 employees and stratified sampling of firms with 10-200 employees. In the years after 1990, special efforts have been devoted to minimizing the incidences of panel exit as well as to including new firms through refreshment samples aimed at preserving a high degree of representativeness for the manufacturing sector at large.[19] The data distinguish between 20 different industries at the 2-digit level of the NACE Rev. 2 classification and six different size groups defined by the average number of workers employed during the year (10-20; 21-50; 51-100; 101-200; 201-500; >500); combinations of industries and size groups serve as strata in the stratification. We express all value variables in constant 2006 prices using firm-level price indexes derived from the survey data or, where necessary, industry-level price indexes derived from the Spanish Instituto Nacional de Estadística (INE).

[19]For details see `https://www.fundacionsepi.es/investigacion/esee/en/spresentacion.asp` (accessed on May

Table 1: Descriptive statistics

	Domestic never-acquired (1)	Foreign before (2)	Foreign after (3)	Observations (1)/(2)/(3) (4)
Production				
Output (in logs)	15.363	17.396	17.812	22,509/502/431
	(1.767)	(1.348)	(1.306)	
Labor productivity (in logs)	2.961	3.302	3.415	22,322/488/414
	(0.669)	(0.684)	(0.652)	
Skill-related variables				
Hires of recent university graduates	0.165	0.400	0.413	22,540/503/431
	(0.371)	(0.490)	(0.493)	
Training engineering	0.167	0.387	0.486	18,505/372/395
	(0.373)	(0.488)	(0.500)	
Training IT	0.153	0.347	0.403	18,503/372/395
	(0.360)	(0.477)	(0.491)	
Training language	0.172	0.487	0.585	18,504/372/395
	(0.377)	(0.500)	(0.493)	
Training marketing	0.089	0.188	0.238	18,505/372/395
	(0.285)	(0.391)	(0.426)	
Training other	0.251	0.447	0.554	18,508/374/397
	(0.434)	(0.498)	(0.498)	
Technology-related variables				
Process innovation: New machines	0.122	0.165	0.162	22,540/503/431
	(0.327)	(0.372)	(0.369)	
Process innovation: New methods of organizing production	0.042	0.083	0.063	22,540/503/431
	(0.202)	(0.277)	(0.243)	
Process innovation: Both new machines and new methods	0.110	0.177	0.216	22,540/503/431
	(0.313)	(0.382)	(0.412)	
Assimilation of foreign technologies	0.093	0.185	0.222	7,270/178/99
	(0.290)	(0.390)	(0.418)	
Market access variables				
Export via foreign parent	0.001	0.013	0.415	4,050/153/94
	(0.031)	(0.114)	(0.495)	
Export	0.570	0.857	0.951	22,517/502/430
	(0.495)	(0.351)	(0.216)	

Notes: This table shows means and standard deviations (in parentheses) of production, skill, technology, and market access variables by ownership status of the firm (never-acquired domestic firms; foreign-acquired firms before the acquisition; foreign-acquired firms after the acquisition). The numbers of observations reported in the final column correspond to the firm-year observations in columns (1), (2) and (3). The sample spans the years 1998-2013 and is restricted to firms that are owned domestically in the first year they enter the sample. Output is a firm's real output value. Labor productivity is the real value added per effective working hour. Hires of recent university graduates is a dummy variable indicating whether the firm hired recent university graduates in a given year. Training engineering, training IT, training language, training marketing, and training other are all dummy variables indicating whether the firm reported positive expenditures on external training in the respective training category in a given year (training other is a residual category capturing any type of training not falling into any of the other categories). The three process innovation variables (new machines; new methods of organizing production; both new machines and new methods) and assimilation of foreign technologies (available every four years) are all dummy variables indicating whether the firm carried out the respective activity in a given year. Export via foreign parent is a dummy variable indicating whether the firm uses the foreign parent as a distribution channel to access foreign markets. As is clear from columns (1) and (2), there are some cases in which the dummy is equal to one for domestically owned firms; these firms are minority-owned by a foreign company. Export is a dummy variable for positive exports.
Source: Authors' computations based on ESEE data.

19, 2017).

We define a firm as foreign owned if a foreign company owns more than 50 percent of its capital. Among all the firms included in our data, 86.2 percent are owned domestically when they first appear in the sample, while 13.8 percent are foreign owned.[20] We exclude the latter group of firms and instead restrict our sample to potential acquisition targets, i.e., those firms that are initially domestic. Among these firms, 97 percent remain domestic throughout the whole period of analysis, while 3 percent become foreign owned.[21]

In Table 1 we pool the data across all years and then sort observations into groups of never-acquired firms (Domestic never-acquired), foreign-acquired firms before the acquisition (Foreign before) and foreign-acquired firms after the acquisition (Foreign after), respectively.[22] We find considerable differences between the three groups, not just in measured output, productivity, and market access, but also in various skill and technology-related activities that importantly determine (future) productivity, but which are rarely observed in firm-level data-sets. The differences between columns (1) and (2) indicate that already before the acquisition foreign-acquired firms are high performers among the group of domestic firms. They are more productive and have a higher propensity to hire recent university graduates, invest in worker training, and innovate. These differences highlight the importance of the selection effect that we address in our empirical analysis. However, the differences that we observe between columns (2) and (3) also indicate the possibility of a treatment effect of foreign ownership. Foreign-acquired firms are consistently more productive, on average, after the acquisition than before the acquisition, and they are more likely to hire recent university graduates, invest in worker training, and innovate. Yet, these differences may be caused by factors unrelated to foreign ownership. Identifying the treatment effect of foreign ownership and establishing causality is one of the main goals of our empirical analysis in the next section.

4 Empirical analysis

Our empirical analysis comes in three steps. First, we estimate the effect of foreign ownership on skill upgrading, and contrast it with the effects of domestic acquisitions as well as foreign divestments.[23] Second, we investigate the channel underlying our results, focusing on the market size effect of foreign ownership. And finally, we estimate the productivity effects when firms engage in both skill and technology upgrading simultaneously.

[20] 3.2 percent of all the firms included in our data are foreign owned by more than zero, but not more than 50 percent, when they first appear in the sample, and thus classified as domestically owned. We have checked that excluding these firms from our analysis leaves our empirical results unchanged.

[21] This amounts to a total of 119 acquisitions. The year 2006 is the year with the highest number of acquisitions (22), but otherwise the acquisitions are distributed quite evenly across the years 1999-2013. In particular, there is no concentration of acquisitions around the crisis years. A small number of domestic firms report changes in the share of capital owned by a foreign company from zero to 25-50%. Including these firms in the group of foreign-acquired firms does not affect our empirical results in any significant way.

[22] In Table A.1 in the Appendix we provide descriptive statistics on further variables we employ in our empirical analysis.

[23] Guadalupe et al. (2012) use the ESEE data for the years 1990-2006 to show that foreign-acquired firms innovate more upon acquisition. We have verified that this result holds also in our sample period (1998-2013). For details see Section S.4 of the online supplement to this paper. For domestic acquisitions and foreign divestments the evidence is less clear (results not reported).

4.1 The effect of foreign ownership on skill upgrading

4.1.1 Foreign acquisitions

We begin by investigating whether firms that become foreign owned engage in skill upgrading. In our theoretical model firms do so through two margins. The first is an increase in the share of high-skilled workers (captured by a decrease in z). The second margin is an increase in worker training (captured by an increase in τ).

In our model the response to the acquisition derives from a direct as well as an indirect effect. The direct effect is the market size effect associated with foreign ownership. It arises because a better trained workforce allows the acquired firm to enjoy disproportionately greater benefits due to a larger market size. The indirect effect, on the other hand, derives from the technology-skill complementarity in our model. Because operating a new and superior technology at maximum efficiency requires a more skilled workforce, acquired firms have an incentive to increase the share of high-skilled workers as well as to intensify worker training whenever they upgrade their production technology in response to the acquisition. In the remainder of this section we aim to demonstrate that acquired firms do exactly this: they hire more high-skilled workers, thereby increasing the skill intensity of the firm, and at the same time they increase worker training.

To identify the effect on the skill intensity of the firm, we proceed in two steps. First, in the main text we use information on whether the firm hired recent university graduates in any given year. This allows us to construct a measure of the stock of high-skilled workers as: $h_{it} = \sum_{j=t_0}^{t} h_{ij}$, where h_{ij} is a 0/1 indicator for hiring of recent university graduates and t_0 is the year the firm enters our sample.[24] Importantly, a firm's number of high-skilled workers at any point in time t is a function of the history of high-skilled workers entering and leaving the workforce, and thus, other things held constant, increasing in h_{it}. The stock of high-skilled workers at time t_0 (i.e., when the firm enters our sample) will be controlled for through firm fixed effects in the estimation. Thus, the effect of foreign ownership that we identify in our empirical model will be a shift in the firm's hiring policy towards fresh university graduates, or, similarly, an increase in the number of high-skilled workers after the acquisition. In the second step of this analysis, and to support our arguments from the first step, we employ the number of workers with different levels of education as well as the share of high-skilled workers in the firm. To save on space, we relegate detailed results corresponding to this second step of the analysis to Appendix A.3.1 (more on this below).

The information on worker training in our data-set is available from 2001 onwards and distinguishes five different types: engineering, IT, marketing, language, and other (a residual category). This allows us to investigate whether acquired firms increase worker training, not just overall, but also specifically in those categories that are closely related to a firm's production technology (viz. engineering and IT). Since past training expenditures contribute positively to the stock of knowledge available in a firm, we proceed as before and construct a measure of the (training-related) stock of knowledge as: $\tau_{it} = \sum_{j=t_0}^{t} \tau_{ij}$, where τ_{ij} is a 0/1 indicator for positive training expenditures (re-

[24] Recent university graduates are defined as recent graduates from a five-year university programme regardless of the field of study.

gardless of the type of training, or in one specific training category, depending on the specification). Thus, our empirical model will identify an increase in the stock of knowledge after the acquisition that the firm would not have produced if it had stayed domestic instead of being acquired by a foreign company.

To establish a causal effect of foreign ownership on the acquired firm's stock of high-skilled workers we estimate the following equation:

$$h_{it} = \gamma F_{it-1} + \boldsymbol{\beta}\mathbf{X}_{it-2} + \eta_i + \eta_{st} + \varepsilon_{it}, \tag{17}$$

and accordingly for the effect on worker training (where we use τ_{it} instead of h_{it} as the dependent variable). In this equation, F_{it-1} is a foreign ownership dummy lagged by one period, η_i is a firm fixed effect, η_{st} is an industry-year fixed effect (to control for general time trends and industry shocks including policy shocks that affect firms operating in the same industry equally), $\mathbf{X}_{it-2}$ is a vector of time-varying firm-level controls (lagged by one period relative to the acquisition and with a corresponding vector of parameters $\boldsymbol{\beta}$ to be estimated), and ε_{it} is an error term with zero conditional mean. Note that industry-specific linear age trends are also controlled for in this specification, as these can be written as $\theta_s \text{Age}_{it} = a_i + b_s t$, which are absorbed by the firm fixed effects along with the industry-year fixed effects. The parameter of interest in Eq. (17) is γ, which captures the effect of a change from domestic to foreign ownership. It indicates the percentage point change in the probability of hiring (in decimal form) one year after the acquisition. Identifying γ from within-firm variation means that all firm-specific factors are controlled for in the estimation as long as they are constant through time (e.g. the exogenous productivity level ϕ in our model, which influences both selection into foreign ownership and skill upgrading).[25]

However, controlling for firm fixed effects is not enough to establish causality, because selection into foreign ownership is likely to be driven, not only by time-constant, but also time-varying factors (e.g. the evolution of firm productivity over time). To address this issue and ensure that our parameter estimates reflect skill upgrading associated with a change from domestic to foreign ownership, we closely follow the empirical methodology proposed by Guadalupe et al. (2012). First, we include the vector $\mathbf{X}_{it-2}$ in the estimation to control for selection on a set of time-varying firm-level characteristics (productivity, productivity growth, average wage, and capital intensity). Second, we augment Eq. (17) by foreign ownership dummies for the current year (F_{it}) as well as for the following year (F_{it+1}). This allows us to investigate whether firms engage in skill upgrading *before* the acquisition. And finally, we combine firm fixed effects with a propensity score reweighting estimator to tackle selection into foreign ownership based on past firm characteristics.

Specifically, we construct propensity scores and reweight each observation in (17) in order to generate the same distribution of important observable characteristics across domestically owned and foreign-owned firms. By matching along observable firm characteristics, we hope to also match the distribution of important unobservable characteristics. To estimate the propensity scores, we consider each year in our panel and sort those firms that become foreign owned in that year into

[25] See Table A.2 in the Appendix for evidence on 'cherry-picking' by foreign investors.

the treatment group and those that always remain domestic into the control group. We then pool observations in the treatment and in the control group across all years and obtain the propensity scores for all firms by running industry-specific probit regressions of foreign ownership (the treatment) on productivity, productivity growth, average wage, capital intensity, year dummies, and the firm's hiring and training decisions (all lagged by one year).[26] As in Guadalupe et al. (2012), we reweight each treated firm by $1/\hat{p}$ and each control firm by $1/(1-\hat{p})$, where $\hat{p}$ is the estimated propensity score.[27]

Table 2 shows the results for our measure of the stock of high-skilled workers (h_{it}) (Panel A), and for worker training (τ_{it}) (Panel B).[28] Both panels are organized in the same way with all columns reporting estimates of variants of Eq. (17). Column (1) controls for firm fixed effects η_i; column (2) adds industry-year fixed effects η_{st}; column (3) adds the time-varying controls contained in $\mathbf{X}_{it-2}$; column (4) adds foreign ownership dummies for the current and the following year; and column (5) applies the propensity score weighting estimator as described above.[29]

Overall, our estimation results consistently show that acquisition by a foreign multinational leads to skill upgrading, both through an increase in the stock of high-skilled workers and through an increase in worker training. More specifically, columns (1) to (3) in Panel A show a positive and significant coefficient of lagged foreign ownership (ranging between +0.33 and +1.28) suggesting a considerable change in the hiring policy towards recent university graduates after the acquisition. Column (4) shows that, while approximately half of the effect materializes in the acquisition year and another half with a one-year lag (the coefficients of F_{it} and F_{it-1} both lie in the vicinity of +0.22), there was no effect taking place in the acquired firm *before* the acquisition (the coefficient of F_{it+1} is equal to -0.09 and not significantly different from zero). Finally, our propensity score estimates in column (5) also show a positive and significant coefficient of lagged foreign ownership, implying that the effect is unlikely to be driven by endogeneity due to selection into foreign ownership. Augmenting the specification in column (5) with foreign ownership dummies for the current and the following year yields results that are very similar to those in column (4) (results not reported).

To substantiate our interpretation that these results indicate a shift in the hiring policy towards high-skilled workers, with a corresponding increase in the skill intensity of acquired firms, we present

[26] In addition to our measures of the stock of high-skilled workers (h_{it-1}) and the stock of knowledge (τ_{it-1}) we include the firm's 0/1 hiring and training decisions in the pre-treatment year as covariates, respectively. We thus allow the propensity scores to depend, not just on the stock of high-skilled workers and the stock of knowledge, but also on recent hiring and training decisions. In a robustness analysis, we have also verified that the results we present in the following are robust, both qualitatively and quantitatively, to including trade- and technology-related variables in the estimation of the propensity scores (viz. the export status and the innovation activities of the firm).

[27] We only keep those observations in the analysis that are in the region of common support, and we have checked that the balancing property is supported by the data in all industries, i.e., all observed characteristics of domestically owned and foreign-owned firms are balanced. Detailed output of the propensity score estimation can be found in Section S.1 of the online supplement to this paper.

[28] Estimates of Eq. (17) in first differences support the results we report here; see Section S.7 of the online supplement to this paper.

[29] Column (4) is always presented with the smallest number of observations due to the leads and lags of the independent variables. In Table S.2 of the online supplement to this paper we present estimates of specifications (1)-(3) using just the observations of the restricted sample in column (4).

Table 2: The effect of foreign acquisitions on hiring and training

	Hires of recent university graduates				
Panel A	(1)	(2)	(3)	(4)	(5)
Lag foreign	1.279***	0.599***	0.331*	0.230	0.416**
	(0.206)	(0.159)	(0.198)	(0.168)	(0.200)
Foreign				0.211*	
				(0.123)	
Forward foreign				-0.0871	
				(0.172)	
Observations	20049	20049	13816	11517	15007
R-squared	0.010	0.366	0.364	0.374	0.427
	Worker training				
Panel B	(1)	(2)	(3)	(4)	(5)
Lag foreign	1.699***	0.731***	0.546**	0.340*	0.890***
	(0.395)	(0.229)	(0.265)	(0.196)	(0.325)
Foreign				0.303*	
				(0.156)	
Forward foreign				0.0280	
				(0.207)	
Observations	17484	17484	13801	11506	13357
R-squared	0.008	0.539	0.540	0.534	0.688
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects		Yes	Yes	Yes	Yes
Time-varying controls			Yes	Yes	
Propensity score					Yes

Notes: In Panel A the dependent variable in all columns is our measure of the stock of high-skilled workers defined as $h_{it} = \sum_{j=t_0}^{t} h_{ij}$, where h_{ij} is a 0/1 indicator variable for hires of recent university graduates. In Panel B the dependent variable in all columns is our measure of the stock of knowledge defined as $\tau_{it} = \sum_{j=t_0}^{t} \tau_{ij}$, where τ_{ij} is a 0/1 indicator variable for positive expenditures on worker training (regardless of the training category). Foreign is a dummy variable for foreign ownership (equal to one if the firm is foreign owned by more than 50 percent and zero otherwise). Time-varying controls include firm-specific productivity, productivity growth, average wage, and capital intensity (all with a two-year lag). For details on the propensity score reweighting estimator see the text. Robust standard errors (in parentheses) are clustered at the firm level. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

a series of additional results in Appendix A.3.1. For this analysis, we use the number of workers with different levels of education as well as the share of high-skilled workers in the firm (i.e. the share of workers with a five-year university degree). These variables are available every four years in our data. We show, first, that while foreign ownership increases the number of workers with a five-year university degree, it does not increase the number of less educated workers, i.e., workers with a Bachelor's degree or no university degree. Secondly, we show that foreign ownership consequently leads to an increase in the skill intensity of the firm, viz. the share of workers with a five-year university degree. Finally, we present results on the effect of foreign ownership on overall firm employment (effective hours worked) as well as on average wages (as a proxy for the share of high-skilled workers). These two variables are available annually in our data and can be used to show that the acquisition has no statistically significant effect on employment, but leads to a significant increase in average wages. Taking stock, it is employment of high-skilled workers and not employment across the board in all worker groups that rises due to foreign ownership.

As for the effect of foreign ownership on worker training, we find similar results as for hiring of high-skilled workers. In Panel B of Table 2 we see a positive and significant coefficient of lagged foreign ownership across all specifications employed. The coefficients in columns (1) to (3) vary between +0.55 and +1.7 indicating a sizeable effect. As before in the case of hiring of recent university graduates we see that almost one half of the training effect materializes in the year of acquisition, and the remaining effect with a one-year lag; see column (4). The propensity score reweighting estimator in column (5) also points towards a highly significant effect of foreign ownership on worker training (with a coefficient of F_{it-1} equal to +0.89). Adding the dummies F_{it} as well as F_{it+1} to the specification in column (5) gives results that are very similar to those in column (4) (results not reported).

Note that in these regressions we do not distinguish between different types of training. This means that the identified effect of foreign ownership might apply to certain types of training, but not to others. A concern would be that it applies just to those types that are not directly related to the firm's production technology (such as marketing or language). To investigate this possibility, we run the same regressions as in Panel B of Table 2 separately for the five different types of training. We find that the effect of foreign ownership is, in fact, not limited to certain types of training. On the contrary, we find that acquired firms intensify worker training across the board in all forms of training (including engineering and IT). In the interest of space we relegate detailed results to Appendix A.3.2.

We also conduct a placebo analysis, where we use the estimated propensity scores to sort the top 5% of non-acquired firms most likely to be acquired into the treatment group, but exclude those firms actually acquired during the sample period. Finding relevant (placebo) effects when estimating Eq. (17) on the thus constructed sample would cast doubt on our interpretation of a causal effect of foreign acquisitions on skill upgrading. However, our estimates reveal no placebo effects, whether we look at hiring, training, skill intensity, or wages as the outcome variable. Details of this analysis can be found in Section S.3 of the online supplement to this paper.[30]

4.1.2 Domestic acquisitions

Having established a significant effect of foreign ownership on skill upgrading, we now ask whether this effect is confined to *foreign* acquisitions or also applies to *domestic* acquisitions. Since we are able to identify domestic acquisitions in our data, we can demonstrate that, in contrast to foreign acquisitions, domestic acquisitions generate no significant skill upgrading once selection is taken into account.

[30]We have also conducted various event study analyses using different control groups in order to explore in more detail the timing of skill upgrading associated with a change in ownership status from domestic to foreign. Two results from these analyses are worth mentioning. First, there is a striking similarity between how hiring and training activities evolve around the acquisition years. Second, the acquisition seems to reverse a monotonic decline in skill upgrading in the years *before* the acquisition. Hiring and training efforts monotonically increase in the years *after* the acquisition. The detailed results of these analyses are available upon request from the authors.

We rely on the same estimation framework as before and restrict the estimation sample to firms not majority-owned by some other firm upon sample entry (potential acquisition targets). Moreover, to generate a suitable control group of never-acquired firms, we exclude all foreign-acquired firms both before and after the acquisition. The estimating equation resembles Eq. (17), where we replace the lagged foreign ownership dummy F_{it-1} by a corresponding domestic dummy D_{it-1} indicating whether the firm is majority-owned by some other (domestic) firm. Since D_{it-1} is not available every year, but every four years, the timing of domestic acquisitions is not precisely identified. However, we observe 118 domestic acquisitions in our estimation sample generating sufficient within-firm variation that we can exploit for identification purposes.

Table 3 shows that, while domestic acquisitions correlate positively with skill upgrading through both hiring and training, there is no robust evidence that this correlation reflects a causal effect. In particular, the coefficient of D_{it-1} is positive and significant for both hiring and training when firm fixed effects as well as industry-year fixed effects are controlled for (columns (1) and (2)), but turns zero (in a statistical sense) once we include time-varying firm-level controls; see column (3). Moreover, when we control for selection through a suitable propensity score reweighting estimator, we find no significant effect of domestic acquisitions on skill upgrading either; see column (4). Addressing selection in this way is crucial due to strong evidence for positive selection on productivity into domestic acquisitions in our data; see Section S.5 of the online supplement to this paper.[31] Hence, our analysis suggests that the positive correlation between domestic acquisitions and skill upgrading reflects 'cherry-picking' on the part of the acquiring firms, rather than skill upgrading in response to the acquisition.[32]

4.1.3 Foreign divestments

To provide yet another angle on the relationship between foreign ownership and skills, we now focus on the effects of foreign *divestments*. These are identified annually in our data and defined in analogy to foreign acquisitions as switches from foreign to domestic ownership. Keeping only those firms in our sample that are in foreign ownership when they enter our data-set, we observe 63 incidences of foreign divestments.

In the context of our analysis, the potential effects of foreign divestments on skill upgrading are interesting for at least two reasons. First, they indicate whether the effects of foreign ownership persist or fade when firms cease to be affiliated with a foreign multinational. Second, they help to discriminate further between skill upgrading in response to acquisitions *per se*, and skill upgrading

[31] To implement the propensity score reweighting estimator, we collapse the data into a single cross-section, sorting those firms that, at some point in time, become majority-owned by some other domestic firm into the treatment group, and all other firms into the control group. We then obtain the propensity scores for all firms by running industry-specific probit regressions of domestic acquisitions (the treatment) on initial productivity controlling for the year of sample entry through a set of dummy variables. As before, we only keep observations in the region of common support and we make sure that the balancing property is supported by the data in all industries.

[32] To address the uncertainty regarding the precise timing of the acquisition, we have also replaced D_{it-1} by the contemporaneous domestic dummy, the first lead, and the second lead, respectively. In no case do we find a significant effect on skill upgrading when selection is controlled for.

Table 3: The effect of domestic acquisitions on hiring and training

	Hires of recent university graduates			
Panel A	(1)	(2)	(3)	(4)
Lag domestic acq.	1.239***	0.447***	-0.084	0.120
	(0.188)	(0.165)	(0.270)	(0.207)
Observations	4805	4805	2190	3638
R-squared	0.037	0.327	0.298	0.493
	Worker training			
Panel B	(1)	(2)	(3)	(4)
Lag domestic acq.	1.898***	0.665***	0.262	0.026
	(0.305)	(0.226)	(0.318)	(0.250)
Observations	3776	3776	2190	2681
R-squared	0.043	0.465	0.427	0.615
Firm fixed effects	Yes	Yes	Yes	Yes
Industry-year fixed effects		Yes	Yes	Yes
Time-varying controls			Yes	
Propensity score				Yes

Notes: In Panel A the dependent variable in all columns is our measure of the stock of high-skilled workers defined as $h_{it} = \sum_{j=t_0}^{t} h_{ij}$, where h_{ij} is a 0/1 indicator variable for hires of recent university graduates. In Panel B the dependent variable in all columns is our measure of the stock of knowledge defined as $\tau_{it} = \sum_{j=t_0}^{t} \tau_{ij}$, where τ_{ij} is a 0/1 indicator variable for positive expenditures on worker training (regardless of the training category). Domestic acq. is a dummy variable equal to one if the firm is majority-owned by some other domestic firm and zero otherwise. Time-varying controls include firm-specific productivity, productivity growth, average wage, and capital intensity (all with a two-year lag). For details on the propensity score reweighting estimator see the text. Robust standard errors (in parentheses) are clustered at the firm level. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

in response to acquisitions by a *foreign* firm.

The estimation results reported in Table 4 suggest that, while foreign divestments do not lead to significant skill *up*grading, there is no evidence either that divested firms significantly *down*grade the skills of their workforce compared to firms that remain in foreign ownership. Overall, we find consistent results across the different estimators and margins of skill upgrading (hiring and training).[33] These estimates further highlight the location of the acquiring firm (domestic vs. foreign) as a crucial factor determining skill investments on the part of the acquired firm. They also suggest that the benefits of foreign ownership do not disappear within a short period of time after the divestment.

4.2 Investigating the channel of skill upgrading

4.2.1 The market size effect

We continue our analysis by investigating what is behind the effect of foreign ownership identified in the previous step of our analysis. The focus of our theoretical model is the market size channel,

[33]To construct the propensity scores used in Table 4, we consider each year in our sample and sort those firms that become domestically owned in that year into the treatment group and those that always remain foreign into the control group. We otherwise proceed analogously to the case of foreign acquisitions in Section 4.1.1.

Table 4: The effect of foreign divestments on hiring and training

	Hires of recent university graduates				
Panel A	(1)	(2)	(3)	(4)	(5)
Lag foreign div.	2.181***	-0.078	-0.178	-0.188	0.960*
	(0.386)	(0.372)	(0.470)	(0.363)	(0.582)
Foreign div.				0.278	
				(0.265)	
Forward foreign div.				-0.243	
				(0.316)	
Observations	3174	3174	2156	1798	2910
R-squared	0.031	0.693	0.686	0.693	0.832
	Worker training				
Panel B	(1)	(2)	(3)	(4)	(5)
Lag foreign div.	3.723***	-0.311	-0.262	-0.099	-0.335
	(0.388)	(0.268)	(0.388)	(0.280)	(0.203)
Foreign div.				-0.123	
				(0.184)	
Forward foreign div.				-0.177	
				(0.252)	
Observations	2662	2662	2146	1790	2511
R-squared	0.054	0.918	0.936	0.935	0.967
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects		Yes	Yes	Yes	Yes
Time-varying controls			Yes	Yes	
Propensity score					Yes

Notes: In Panel A the dependent variable in all columns is our measure of the stock of high-skilled workers defined as $h_{it} = \sum_{j=t_0}^{t} h_{ij}$, where h_{ij} is a 0/1 indicator variable for hires of recent university graduates. In Panel B the dependent variable in all columns is our measure of the stock of knowledge defined as $\tau_{it} = \sum_{j=t_0}^{t} \tau_{ij}$, where τ_{ij} is a 0/1 indicator variable for positive expenditures on worker training (regardless of the training category). Foreign div. is a dummy variable for foreign divestment (equal to one if the firm is domestically owned by more than 50 percent and zero if the firm is foreign owned). Time-varying controls include firm-specific productivity, productivity growth, average wage, and capital intensity (all with a two-year lag). For details on the propensity score reweighting estimator see the text. Robust standard errors (in parentheses) are clustered at the firm level. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

which implies that foreign market access through the foreign parent provides incentives for acquired firms to engage in skill upgrading. In this section we aim to show that it is this channel, rather than foreign ownership per se, which leads to skill upgrading.

We apply two different strategies to pinpoint the market size channel as the driving force behind the effect of foreign ownership on skill upgrading. The first strategy is to show that foreign ownership *interacts* with the export status of the acquired firm, in the sense that among the set of acquired firms it is only those firms exporting (or starting to export) that engage in skill upgrading. Those firms serving only the domestic market before and after the acquisition, in contrast, do not exhibit a different behavior than never-acquired firms. The second strategy is to use explicit information available in the ESEE data on how firms access foreign markets (through the foreign parent or through other means), and to show that it is only those firms using their foreign parents to access foreign markets which experience significant skill upgrading. Importantly, we find consistent evidence for the market size effect across both margins of skill upgrading: hiring of high-skilled workers *and* worker training.[34]

Table 5: The market size effect on hiring and training

	Hires of recent university graduates					
Panel A	(1)	(2)	(3)	(4)	(5)	(6)
Export via foreign parent					0.981*	0.682*
					(0.501)	(0.397)
Lag foreign		0.608***	-0.320	-0.677	0.730	0.148
		(0.158)	(0.472)	(0.672)	(0.514)	(0.355)
Export	0.110**	0.0932*	0.0872	0.00961		
	(0.0550)	(0.0562)	(0.0557)	(0.0590)		
Export × Lag foreign			0.989*	1.090		
			(0.507)	(0.700)		
Observations	23449	20029	20029	13802	1830	2307
R-squared	0.372	0.366	0.367	0.366	0.496	0.549
	Worker training					
Panel B	(1)	(2)	(3)	(4)	(5)	(6)
Export via foreign parent					0.942**	0.636*
					(0.446)	(0.335)
Lag foreign		0.743***	-0.507	-0.662	0.563	0.440
		(0.224)	(0.424)	(0.437)	(0.516)	(0.496)
Export	0.115	0.100	0.0904	0.0195		
	(0.0739)	(0.0804)	(0.0801)	(0.0963)		
Export × Lag foreign			1.334***	1.305***		
			(0.452)	(0.477)		
Observations	19249	17467	17467	13787	1822	2298
R-squared	0.539	0.539	0.540	0.541	0.641	0.704
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time-varying controls				Yes	Yes	
Propensity score						Yes

Notes: In Panel A the dependent variable in all columns is our measure of the stock of high-skilled workers defined as $h_{it} = \sum_{j=t_0}^{t} h_{ij}$, where h_{ij} is a 0/1 indicator variable for hires of recent university graduates. In Panel B the dependent variable in all columns is our measure of the stock of knowledge defined as $\tau_{it} = \sum_{j=t_0}^{t} \tau_{ij}$, where τ_{ij} is a 0/1 indicator variable for positive expenditures on worker training (regardless of the training category). Foreign is a dummy variable for foreign ownership (equal to one if the firm is foreign owned by more than 50 percent and zero otherwise). Export via foreign parent is a dummy variable indicating whether the firm uses the foreign parent as a distribution channel to access foreign markets. Export is a dummy variable for positive exports. Time-varying controls include firm-specific productivity, productivity growth, average wage, and capital intensity (all with a two-year lag). For details on the propensity score reweighting estimator see the text. Robust standard errors (in parentheses) are clustered at the firm level. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

[34]To further underpin this analysis, we also examine changes in export behavior triggered by the acquisition. In line with our theoretical model and the idea that foreign ownership improves foreign market access, we find that firms are more likely to export, serve more export destinations, and increase their total export volume after the acquisition. Detailed results are relegated to Section S.6 of the online supplement to this paper.

More specifically, in the first four columns of Panel A in Table 5 we regress our measure of the stock of high-skilled workers (h_{it}) on firm-level dummies for export status and foreign ownership (lagged by one year). As before, we use firm fixed effects, industry-year fixed effects, and a set of time-varying firm-level controls (lagged by two years). Export status alone enters the regression with a positive and significant coefficient indicating that firms starting to export hire more high-skilled workers; see column (1). This effect survives in column (2) where we bring in foreign ownership, which itself enters with a positive and highly significant coefficient equal to +0.61. More importantly, when we interact the two variables we find that the interaction effect is positive and significant, standing at +0.99, while the main effects of both export status and foreign ownership enter insignificantly. This finding suggests that it is not the acquisition alone that triggers a change in the firm's hiring policy, but rather improved access to foreign markets facilitated by the foreign parent. In column (4) the coefficient of the interaction term loses its significance, but, as we have verified, this is due to the reduced sample size relative to column (3), not the inclusion of time-varying firm-level characteristics.[35]

In the last two columns of Panel A in Table 5 we use explicit information on how the firm accesses the export market. This information is available in the ESEE data not every year, but every four years, which is why we lose several observations in this analysis. In the estimations we include the standard set of controls, lagged foreign ownership, and a 0/1 indicator variable for whether the firm uses the foreign parent in serving foreign markets. The effect of export status as such cannot be identified in this estimation, as all acquired firms that start exporting do so through their foreign parent. Foreign ownership, in contrast, is not collinear with exporting through the foreign parent, which allows us to include the two variables simultaneously. We find a positive and significant effect of exporting through the foreign parent, both with the standard fixed effects estimator and the propensity score weighting estimator. In contrast, the coefficient of the foreign ownership dummy, while positive, is no longer significant (in a statistical sense).

We find an almost identical pattern in Panel B of Table 5, which shows the effects on worker training (i.e., on our measure of the stock of knowledge, τ_{it}). In particular, we find a positive and highly significant interaction effect between export status and foreign ownership (while the main effects of the two variables are insignificant), as well as a positive and significant effect of exporting through the foreign parent (regardless of the estimator used). Hence, foreign ownership triggers worker training, but the market size channel seems to be crucial also for this result.[36]

4.2.2 Other channels

While our model and the above empirical analysis focus on the market size channel, there are at least two other prominent channels that could explain why foreign ownership triggers skill upgrading: technology transfers from the foreign parent to the acquired firm and improved access to finance. It would be relatively straightforward to incorporate these channels into our theoretical model.

[35]Notice that the interaction effect is identified through both continuous exporters and export switchers.

[36]We report regression results for the market size effect on different types of worker training in Appendix A.4.

However, we now provide evidence that, at least in the Spanish context, neither technology transfers nor improved access to finance seem to be driving the effect of foreign ownership on skill upgrading.

If skills and technology are complements and the foreign parent transfers its superior technology to the acquired firm, then this could also explain the effect of foreign ownership on skill upgrading identified in Section 4.1. To investigate this possibility, we have augmented the specifications in columns (5) and (6) of Table 5 by a 0/1 indicator variable for assimilation of foreign technology available in ESEE data every four years. We have also interacted this variable with the foreign ownership dummy, as assimilation of foreign technology is an activity that is not limited to firms in foreign ownership. The results indicate no skill upgrading associated with technology transfer from the foreign owner to the acquired firm. Detailed regression output can be found in Appendix A.5.1.

In the presence of financial frictions, foreign ownership can alleviate credit constraints by improving access to finance, e.g. through the internal capital market of the foreign multinational or better access to foreign capital markets. To the extent that skill and technology investments are held back by lack of financial resources, we should observe a more positive development in these activities in response to the acquisition. Our strategy to identify the financial channel in our data is twofold. First, we investigate whether foreign-acquired firms display a different evolution regarding key financial figures (debt share, debt maturity, and debt service ratio) relative to non-acquired firms. We find no differential changes in these variables in response to the acquisition. Secondly, we investigate whether the financial situation of the firm at the time of the acquisition mediates the effect of foreign ownership on skill upgrading. This allows us to see whether, among the group of acquired firms, those likely to be credit constrained before the acquisition display a steeper increase in skill investments (as we would expect if foreign ownership mitigates credit constraints). Our regression results indicate that this is not the case. Overall, these findings square well with the fact that foreign multinationals do 'cherry-picking', i.e., they acquire those firms unlikely to be credit constrained. We relegate detailed regression output to Appendix A.5.2.

Taken together, our results clearly suggest that it is the market size effect rather than other plausible channels that triggers skill upgrading within foreign-acquired firms. Our evidence importantly complements the findings in Guadalupe et al. (2012) that acquired firms innovate more upon acquisition (which is likewise driven by the market size channel). While both effects, skill upgrading and innovation, thus seem to be caused by the same underlying factor (viz. access to a larger market through foreign ownership), the two effects might also reinforce each other. Our theoretical model incorporates this possibility by introducing a complementarity between innovation and the skill intensity of the firm, as well as between innovation and worker training. To shed some more light on these complementarities is the purpose of the next step of our analysis.

4.3 The output and productivity effects of both skill and technology upgrading

We now look into the output and productivity effects associated with both skill and technology upgrading. This part of our analysis is motivated by the technology-skill complementarity postulated in our theoretical model. In particular, our model suggests that firms raise their output and their productivity by engaging in both innovation and skill upgrading simultaneously. In the following regression analysis we wish to show that the evolution of output and productivity is indeed determined by a crucial interaction between innovation and skill upgrading. The results we present in the following are consistent with the hypothesis of skill-biased technological change induced by foreign ownership, i.e., shifts in the technological frontier that favor the relative productivity of skilled over unskilled labor.

Specifically, Eq. (8) relates firm output to the firm's baseline productivity level ϕ as well as an endogenous productivity term φ, which is a function of the assignment of skills to tasks (z) (and thus the firm's skill intensity), the technology level (λ), and the level of worker training (τ); see Eq. (9). As we have demonstrated above, foreign ownership causes adjustments in all of these variables, viz. a decrease in z, an increase in λ, and an increase in τ. Hence, we expect to find significant output effects of foreign ownership. As a first step, we thus run regressions that resemble our earlier analysis of the effect of foreign ownership on skill upgrading, but now we look at output as the outcome variable. The evidence we present in the first three columns of Table 6 is consistent with a sizable output effect of foreign ownership. To be more precise, in column (1) we employ the standard fixed effects estimator and regress the natural log of output on lagged foreign ownership. Hence, the exogenous baseline productivity ϕ is controlled for, and we relate changes in output over time within a firm to changes in ownership. We also include industry-year dummies, which means we control for industry-specific output shocks and identify deviations from the evolution of output within an industry. In column (2) we include the average wage and capital intensity as firm-level controls (lagged by two years), and in column (3) we employ the propensity score weighting estimator as described in Section 4.1.1. Across all three specifications, we find statistically significant output effects of foreign ownership in the vicinity of 11 to 15 percent.

To show that these output effects are, indeed, the result of the adjustments in z, λ, and τ as described in our theoretical model, we augment our estimation to include a measure of the technology level of the firm along with our measures of the stock of high-skilled workers and the stock of knowledge, respectively. The ESEE data provide a wide variety of information on specific innovation activities of the firm. Our focus is on process innovation, which may refer to the introduction of new machines or the implementation of new methods of organizing production, or both. We follow Guadalupe et al. (2012) in assuming that the firm's level of technology at any point in time t is the result of the sum of all innovations that have taken place up to that point: $\rho_{it} = \sum_{j=t_0}^{t} \rho_{ij}$, where ρ_{ij} is a 0/1 indicator for process innovation. The use of within-firm variation in this analysis means that the levels of technology and skills when the firm enters the sample in t_0 are controlled for, and that we relate *changes* in output to *changes* in technology and skills within a firm over time.[37]

We present the results in the remaining columns (4) to (7) of Table 6.[38] Three important insights

[37] We add one to the technology level ρ_{it} before taking the log to keep observations with zero innovation in the regressions, and accordingly for our measures of the stock of high-skilled workers h_{it} and the stock of knowledge τ_{it}, respectively. However, the results do not change in any significant way when we exclude these observations from the estimation.

[38] In these columns we augment the specification of column (2), but we get virtually identical results when we

Table 6: The output effects of skill upgrading and process innovation

	Output (in logs)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Lag foreign	0.148***	0.111**	0.124*	0.0808	0.0761	0.0753	0.0685
	(0.0545)	(0.0561)	(0.0661)	(0.0552)	(0.0547)	(0.0581)	(0.0578)
Process innovation				0.214***	0.159***	0.244***	0.183***
				(0.0254)	(0.0280)	(0.0278)	(0.0326)
Hiring				0.179***	0.0482		
				(0.0325)	(0.0430)		
Hiring × Process innovation					0.0759***		
					(0.0198)		
Training						0.105***	0.0399
						(0.0212)	(0.0263)
Training × Process innovation							0.0506***
							(0.0155)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-varying controls		Yes		Yes	Yes	Yes	Yes
Propensity score			Yes				
Observations	20023	16480	14993	16480	16480	15317	15317
R-squared	0.231	0.255	0.227	0.282	0.285	0.291	0.294

Notes: The dependent variable in all columns is firm-specific output (in logs) expressed in 2006 prices using firm-level price indexes. Foreign is a dummy variable for foreign ownership (equal to one if the firm is foreign owned by more than 50 percent and zero otherwise). Process innovation ($\ln[1+\rho_{it}]$) is a measure of the technology level of the firm with $\rho_{it} = \sum_{j=t_0}^{t} \rho_{ij}$, where ρ_{ij} is a 0/1 indicator for process innovation. Hiring ($\ln[1+h_{it}]$) is a measure of the stock of high-skilled workers with $h_{it} = \sum_{j=t_0}^{t} h_{ij}$, where h_{ij} is a 0/1 indicator variable for hires of recent university graduates. Training ($\ln[1+\tau_{it}]$) is a measure of the stock of knowledge with $\tau_{it} = \sum_{j=t_0}^{t} \tau_{ij}$, where τ_{ij} is a 0/1 indicator variable for positive expenditures on worker training (regardless of the training category). Time-varying controls include average wage and capital intensity (all with a two-year lag). For details on the propensity score reweighting estimator see the text. Robust standard errors (in parentheses) are clustered at the firm level. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

emerge from this analysis. The first is that both technology and skill upgrading raise firm output. This can be seen in columns (4) and (6), which show that all respective variables enter the equation with a precisely estimated and positive coefficient. The second insight is that—consistent with our model—the output gains are largest when firms engage in both technology and skill upgrading at the same time. This can be seen in columns (5) and (7) where we interact the level of technology with the stock of high-skilled workers and the stock of knowledge, respectively. These columns reveal highly significant and positive coefficients of the respective interaction terms, i.e., we find clear evidence for a skill bias in technological change. The final insight from this analysis is that the output effects due to technology and skill upgrading seem to absorb the output effect of foreign ownership. This is evidenced by the reduced point estimates of the coefficient of the foreign ownership dummy in all columns (4) to (7). In fact, in these regressions we cannot reject the null hypothesis that the output effect of foreign ownership is zero. This result highlights the role of endogenous technology and skill adjustments in explaining the strong post-acquisition performance in foreign-owned firms.

instead augment the propensity score weighting estimator employed in column (3).

To see whether and to what extent these results reflect a productivity effect, and not just a scale effect, we have replicated Table 6 using a standard measure of total factor productivity (TFP) as employed in the literature. We find essentially the same picture with TFP as with output, and in particular the significant interaction effects between technology and skill upgrading go through in these regressions. To save on space, we relegate further information on this exercise and detailed regression output to Appendix A.6.[39]

5 Conclusion

In this paper we develop a model of foreign ownership and skill-biased technological change in which heterogeneous firms decide endogenously about the level of technology, the share of high-skilled workers in production, and the level of worker training. A crucial feature of our model is a technology-skill complementarity which implies that adopting new and superior technology creates incentives for firms to enhance workforce skills (through both hiring of high-skilled workers and worker training). The model can be used to study the effects of foreign acquisitions on technology and skill choices within firms, and to identify the sources of productivity gains at the micro level. We test the implications of our model on a longitudinal firm-level data-set from Spain and find evidence strongly supportive of the model.

By focusing attention on endogenous skill adjustments within foreign-acquired firms, we believe that our paper speaks to the public debate about the costs and benefits of multinational firm activity and foreign acquisitions. There seems to be a widespread concern that foreign acquisitions may harm domestic workers through job losses and wage cuts. While our paper does not lend itself to an analysis of the distributional effects of foreign acquisitions or their welfare consequences, it nevertheless paints a nuanced picture of the within-firm skill changes caused by foreign acquisitions. On the one hand, we find an increase in the relative demand for high-skilled labor. This finding refers to the classical distinction between high- and low-skilled labor based on the formal education of workers. On the other hand, we also find a significant increase in worker training. This dimension has often been neglected in the debate about the implications of skill-biased technological change, although worker training provides a direct and positive stimulus for the stock of human capital available in a country.

We should like to emphasize that, in the large set of estimations we have carried out for this research, we have found the two dimensions of skill upgrading (hiring and training) to behave remarkably similar. While this is consistent with our theoretical model, one might still wonder whether (and under which conditions) the two margins can behave differently. Answering this question is left for future research.

[39] In Appendix A.6 we have also augmented the estimations in Table 6 to include labor (measured by the number of effective working hours; in logs) to control for the scale of the operations. To relax the assumption of strict exogeneity included in the regressions in Table 6 we have also treated the technology and skill variables as predetermined variables or as endogenous variables in a simple fixed-effects IV framework using lags as instruments. It turns out that this does very little to our estimates.

References

Acemoglu, Daron. (2003). 'Patterns of skill premia', *Review of Economic Studies* 70(2), 199–230.

Acemoglu, Daron and Autor, David H. (2011), Chapter 12 - Skills, tasks and technologies: Implications for employment and earnings, *in* **Orley Ashenfelter and David Card**., eds, 'Handbooks in Economics Handbook of Labor Economics', Vol. 4, Part B, Elsevier, pp. 1043–1171.

Akerman, Anders, Gaarder, Ingvil and Mogstad, Magne. (2015). 'The skill complementarity of broadband internet', *Quarterly Journal of Economics* 130(4), 1781–1824.

Almeida, Rita. (2007). 'The labor market effects of foreign owned firms', *Journal of International Economics* 72(1), 75–96.

Antràs, Pol. (2015), *Global production: Firms, contracts, and trade structure*, Princeton University Press.

Arnold, Jens M. and Javorcik, Beata S. (2009). 'Gifted kids or pushy parents? Foreign direct investment and plant productivity in Indonesia', *Journal of International Economics* 79(1), 42–53.

Autor, David H., Levy, Frank and Murnane, Richard J. (2003). 'The skill content of recent technological change: An empirical exploration', *Quarterly Journal of Economics* 118(4), 1279–1333.

Bas, Maria. (2012). 'Technology adoption, export status, and skill upgrading: Theory and evidence', *Review of International Economics* 20(2), 315–331.

Blonigen, Bruce A. and Slaughter, Matthew J. (2001). 'Foreign-affiliate activity and US skill upgrading', *Review of Economics and Statistics* 83(2), 362–376.

Bøler, Esther A. (2015). 'Technology-skill complementarity in a globalized world'. University of Oslo, mimeo.

Bond, Stephen and Van Reenen, John. (2007). 'Microeconometric models of investment and employment', *Handbook of Econometrics* 6, 4417–4498.

Brakman, Steven, Garretsen, Harry, Gerritse, Michiel, van Marrewijk, Charles et al. (2018), A model of heterogeneous firm matches in cross-border mergers & acquisitions, CESifo Working Paper No. 7083.

Bustos, Paula. (2011). 'Trade liberalization, exports, and technology upgrading: Evidence on the impact of MERCOSUR on Argentinian firms', *American Economic Review* 101(1), 304–40.

Caves, Richard E. (1996), *Multinational enterprise and economic analysis*, Cambridge university press.

Delgado, Miguel A., Fariñas, Jose C. and Ruano, Sonia. (2002). 'Firm productivity and export markets: A non-parametric approach', *Journal of International Economics* 57(2), 397–422.

Fabbri, Francesca, Haskel, Jonathan E. and Slaughter, Matthew J. (2003). 'Does nationality of ownership matter for labor demands?', *Journal of the European Economic Association* 1(2-3), 698–707.

Garicano, Luis and Steinwender, Claudia. (2016). 'Survive another day: Using changes in the composition of investments to measure the cost of credit constraints', *Review of Economics and Statistics* 98(5), 913–924.

Goldin, Claudia and Katz, Lawrence F. (2007). 'Long-run changes in the wage structure: Narrowing, widening, polarizing', *Brookings Papers on Economic Activity* 38(2), 135–168.

Guadalupe, Maria, Kuzmina, Olga and Thomas, Catherine. (2012). 'Innovation and foreign ownership', *American Economic Review* 102(7), 3594–3627.

Harrison, Ann E. and McMillan, Margaret S. (2003). 'Does direct foreign investment affect domestic credit constraints?', *Journal of International Economics* 61(1), 73–100.

Heyman, Fredrik, Sjöholm, Fredrik and Tingvall, Patrik G. (2007). 'Is there really a foreign ownership wage premium? Evidence from matched employer-employee data', *Journal of International Economics* 73(2), 355–376.

Hijzen, Alexander, Martins, Pedro S., Schank, Thorsten and Upward, Richard. (2013). 'Foreign-owned firms around the world: A comparative analysis of wages and employment at the micro-level', *European Economic Review* 60, 170–188.

Huttunen, Kristiina. (2007). 'The effect of foreign acquisition on employment and wages: Evidence from Finnish establishments', *Review of Economics and Statistics* 89(3), 497–509.

Ichniowski, Casey, Bartel, Ann and Shaw, Kathryn. (2007). 'How does information technology really affect productivity? Plant-level comparisons of product innovation, process improvement and worker skills', *Quarterly Journal of Economics* 122(4), 1721–1758.

Koch, Michael. (2016). 'Skills, tasks and the scarcity of talent in a global economy', *Review of International Economics* 24(3), 536–563.

Kohler, Wilhelm and Smolka, Marcel. (2014). 'Global sourcing and firm selection', *Economics Letters* 124(3), 411–415.

Levy, Frank and Murnane, Richard J. (1996). 'With what skills are computers a complement?', *American Economic Review* 86(2), 258–262.

Lewis, Ethan. (2011). 'Immigration, skill mix, and capital skill complementarity', *Quarterly Journal of Economics* 126(2), 1029–1069.

Lileeva, Alla and Trefler, Daniel. (2010). 'Improved access to foreign markets raises plant-level productivity… for some plants', *Quarterly Journal of Economics* 125(3), 1051–1099.

Neary, J Peter. (2007). 'Cross-border mergers as instruments of comparative advantage', *Review of Economic Studies* 74(4), 1229–1257.

Nocke, Volker and Yeaple, Stephen R. (2007). 'Cross-border mergers and acquisitions vs. greenfield foreign direct investment: The role of firm heterogeneity', *Journal of International Economics* 72(2), 336–365.

Olley, G. Steven and Pakes, Ariel. (1996). 'The dynamics of productivity in the telecommunications equipment industry', *Econometrica* 64(6), 1263–1297.

Taylor, Karl and Driffield, Nigel. (2005). 'Wage inequality and the role of multinationals: Evidence from UK panel data', *Labour Economics* 12(2), 223–249.

Yeaple, Stephen R. (2005). 'A simple model of firm heterogeneity, international trade, and wages', *Journal of International Economics* 65(1), 1–20.

A Appendix

A.1 Further descriptive statistics

Table A.1: Further descriptive statistics

	Domestic never-acquired	Foreign before	Foreign after	Observations (1)/(2)/(3)
	(1)	(2)	(3)	(4)
# workers with Master's degree	8.644	21.194	39.576	7,264/176/99
	(41.326)	(35.783)	(58.341)	
# workers with Bachelor's degree	10.024	28.295	43.512	7,264/176/99
	(47.060)	(53.148)	(73.380)	
# non-graduated workers	98.902	277.965	363.599	7,264/176/99
	(258.551)	(384.68)	(492.746)	
Share of high-skilled workers	0.048	0.065	0.085	7,269/176/99
	(0.075)	(0.063)	(0.074)	
Labor (in logs)	11.278	12.748	13.000	22,494/498/425
	(1.287)	(1.070)	(1.021)	
Capital intensity (in logs)	3.178	3.817	3.967	21,911/478/405
	(1.178)	(0.971)	(0.863)	
Total factor productivity (in logs)	12.618	14.444	14.797	21,816/477/404
	(1.888)	(1.359)	(1.627)	
Labor productivity growth	-0.007	-0.011	0.005	18,935/384/401
	(0.528)	(0.599)	(0.523)	
Average wage (in logs)	2.672	2.999	3.120	22,383/496/424
	(0.398)	(0.333)	(.315)	
Exports (in logs)	7.972	13.620	15.380	22,517/502/430
	(7.201)	(5.885)	(4.196)	
# export destinations	0.657	1.068	1.244	22,540/503/431
	(0.997)	(1.131)	(0.990)	
Debt share	0.557	0.575	0.561	19,148/392/395
	(0.239)	(0.229)	(0.229)	
Debt maturity	0.752	0.806	0..796	19,855/416/416
	(0.236)	(0.214)	(0.244)	
Debt service ratio	0.893	0.549	0.462	16,721/332/393
	(34.988)	(0.561)	(0.468)	

Notes: This table shows means and standard deviations (in parentheses) for different variables by ownership status of the firm (never-acquired domestic firms; foreign-acquired firms before the acquisition; foreign-acquired firms after the acquisition). The numbers of observations reported in the final column correspond to the firm-year observations in columns (1), (2) and (3). The sample spans the years 1998-2013 and is restricted to firms that are owned domestically in the first year they enter the sample. High-skilled workers are workers with a five-year university degree (Master's degree). Labor is the number of effective working hours. Capital intensity is the capital (the value of land, buildings, and other capital such as equipment and machinery) per effective working hour. Total factor productivity (TFP) is estimated by the Olley and Pakes (1996) estimation routine. Labor productivity growth is the annual growth rate of real value added per effective working hour. Average wage is the real total wage bill per worker. Exports is the export volume reported by the firms, where we add one before taking logs to keep zero observations. # export destinations is the number of foreign markets served by the firm. Debt share is defined as total debt over total assets, debt maturity is defined as the ratio of short-term debt over total debt and debt service ratio is defined as the sum of debt and interest payments over total sales.
Source: Authors' computations based on ESEE data.

A.2 'Cherry-picking' by foreign investors

In Table A.2 we test whether foreign firms acquire the most productive firms in Spain in our sample period from 1998-2013. This analysis replicates Table 2 on p. 3608 in Guadalupe et al. (2012) who use an earlier sample period (1990-2006). Besides small deviations in the point estimates the significance of the coefficients remains unaffected by the change in the sample period, which provides evidence for 'cherry-picking' by foreign investors.

More specifically, Panel A reports estimates of an equation of the following form:

$$F_i = \alpha + \beta\phi_{i0} + d_s + \epsilon_i, \tag{A.1}$$

where F_i is a 0/1 indicator variable for whether firm i was acquired by a foreign company during the sample period (meaning a change in the foreign ownership share to more than 50 percent), ϕ_{i0} is the firm's productivity level in the year of sample entry, α and β are parameters to be estimated, d_s is an industry fixed effect, and ϵ_i is the error term. Productivity in these regressions is measured by the log of sales (columns (1) to (3)) or the log of labor productivity (columns (4) to (6)).

Panel B reports estimates of an equation of the following form:

$$F_{it} = \alpha + \beta\phi_{it-1} + d_{st} + \epsilon_{it}, \tag{A.2}$$

where the dependent variable now refers to the foreign ownership status of firm i in year t (equal to one if the firm is foreign owned by more than 50 percent and zero otherwise), ϕ_{it-1} is lagged productivity, and d_{st} is an industry-year fixed effect.

Table A.2: The selection decision: linear probability specification

	ln sales			ln labor productivity		
Productivity measure	(1a)	(2a)	(3a)	(4a)	(5a)	(6a)
Panel A. The probability of being acquired during the sample period						
Base year productivity	0.0208***		0.0154***	0.0188***		0.0189***
	(0.00249)		(0.00367)	(0.00522)		(0.00591)
2nd quartile base year productivity		0.0153***			0.00707	
		(0.00482)			(0.00643)	
3rd quartile base year productivity		0.0332***			0.0227***	
		(0.00659)			(0.00753)	
4th quartile base year productivity		0.0817***			0.0341***	
		(0.00991)			(0.00837)	
Exporting firm in base year			0.00567			0.0259***
			(0.00815)			(0.00629)
Exporting in base year × base year productivity			0.00862*			-0.00937
			(0.00481)			(0.00984)
Observations	3349	3349	3349	3304	3304	3304
R^2	0.051	0.045	0.052	0.019	0.021	0.026
	(1b)	(2b)	(3b)	(4b)	(5b)	(6b)
Panel B. The probability of being acquired in a given year						
Lagged productivity	0.00394***		0.00355***	0.00461***		0.00403***
	(0.000511)		(0.000883)	(0.00122)		(0.00141)
2nd quartile lagged productivity		0.00314***			0.000810	
		(0.000872)			(0.00106)	
3rd quartile lagged productivity		0.00784***			0.00607***	
		(0.00155)			(0.00149)	
4th quartile lagged productivity		0.0170***			0.00864***	
		(0.00225)			(0.00195)	
Lag exporting firm			-0.000559			0.00434***
			(0.00192)			(0.00132)
Lag exporting firm × lagged productivity			0.000702			-0.000833
			(0.00103)			(0.00217)
Observations	19685	19685	19668	19538	19538	19522
R^2	0.014	0.013	0.014	0.008	0.009	0.009
Industry FEs (both panels) and year FEs and industry trends (in panel B)	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Foreign is a dummy variable for foreign ownership (equal to one if the firm is foreign owned by more than 50 percent and zero otherwise). Base year (lagged) ln sales is the natural logarithm of firm's real sales, relative to the industry mean, in the first year the firm appears in the sample (one year prior to the dependent variable). Base year (lagged) labor productivity is the natural logarithm of real value added per worker, relative to the industry mean, in the first year the firm appears in the sample (one year prior to the dependent variable). Exporting firm in base year equals one if the firm was an exporter in the first year it appears in the sample. Lag exporting firm equals one if the firm was an exporter the previous year. The first year the firm appears in the sample is dropped from all regressions. Panel B regressions condition on the firm being not foreign owned in the previous year. Standard errors are clustered by firm. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

A.3 Further results on the effect of foreign ownership on skill upgrading

A.3.1 Skill intensity

In Panel A of Table 2 we identify the effect of foreign ownership on the firm's hiring of fresh university graduates. We interpret the evidence that we find as indicating a shift in the hiring policy towards high-skilled workers, and thus as an increase in the skill intensity of the firm (corresponding to a decrease in the threshold value z in our theoretical model). The evidence we present in the following substantiates this interpretation.

We begin by investigating whether foreign-acquired firms aim to increase not only the number of high-skilled workers (those with a five-year university degree), but also the number of less skilled workers. We do so by using information available in the ESEE data on the number of workers with different levels of education (viz. those with a Master's degree, a Bachelor's degree, and non-graduates). This information allows for a more explicit test of the implications of our model for the effect of foreign acquisitions on the skill intensity of the firm. The ESEE data include this information every four years, with 1998 being the first year we observe the variable in our sample. Since we use lagged foreign ownership in the regressions, this implies that we have up to three observations per firm in the data (2002, 2006, 2010). The regression results reported in Table A.3 indicate a clear tendency among acquired firms to increase the number of high-skilled workers. The point estimates in columns (1) and (2) indicate an increase in the number of workers with a Master's degree by 83% and 151%, respectively. This is a substantial effect indicating considerable hiring efforts. In contrast, columns (3) to (6) suggest that there is no significant change in the number of less educated workers, viz. workers with a Bachelor's degree or no university degree.

This finding is further corroborated by the results we obtain when using a direct measure of skill intensity as the dependent variable, viz. the share of high-skilled workers (defined as the share of workers with a five-year university degree; in logs). This variable has the advantage that it is directly related to the measure of skill intensity used in our model; see Eq. (7). Again the ESEE data include this information every four years (see above). A potential problem is that the information could suffer from heaping, i.e., some firms round the share of high-skilled workers introducing measurement error in the data. The regression results reported in columns (1) and (2) of Table A.4 nevertheless indicate a tendency among acquired firms to increase the share of high-skilled workers. We find a positive coefficient of lagged foreign ownership in both specifications, and the coefficient is significantly different from zero. The point estimates in columns (1) and (2) indicate an increase by 75% and 146%, respectively. Hence, a firm with a share of high-skilled workers equal to 5% will end up with a share of high-skilled workers between 8.75% and 12.3% due to the acquisition. Finally, we also investigate the impact of foreign ownership on employment (measured by the number of effective working hours) and average wages in columns (3) to (6). The coefficient of lagged foreign ownership on the log of employment is positive, but not statistically different from zero. Hence, we cannot reject the null hypothesis that acquired firms do not expand their overall employment. However, when we use the log of average wages as a rough proxy for skill

Table A.3: The effect of foreign ownership on the number of workers with master or bachelor degree and the number of non-graduate workers

	Master		Bachelor		Non-graduates	
	(1)	(2)	(3)	(4)	(5)	(6)
Lag foreign	0.830*	1.514**	-0.182	-0.109	0.131	0.0185
	(0.477)	(0.680)	(0.239)	(0.270)	(0.136)	(0.0813)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time-varying controls	Yes		Yes		Yes	
Propensity score		Yes		Yes		Yes
Observations	2049	1653	1927	1561	3119	2491
R-squared	0.102	0.130	0.076	0.106	0.249	0.273

Notes: The different dependent variables used are the numbers of workers with a Master's degree (defined as workers with a five-year university degree), a Bachelor's degree, or no university degree (all in logs). Foreign is a dummy variable for foreign ownership (equal to one if the firm is foreign owned by more than 50 percent and zero otherwise). Time-varying controls include firm-specific productivity, productivity growth, average wage, and capital intensity (all with a two-year lag). For details on the propensity score reweighting estimator see the text. Robust standard errors (in parentheses) are clustered at the firm level. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

intensity, the coefficient is positive and significant.

Table A.4: The effect of foreign ownership on the share of high-skilled workers, employment and average wages

	Share high-skilled		Employment		Average wage	
	(1)	(2)	(3)	(4)	(5)	(6)
Lag foreign	0.750*	1.456**	0.0330	0.0331	0.0403*	0.0765*
	(0.413)	(0.651)	(0.0505)	(0.0609)	(0.0218)	(0.0368)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time-varying controls	Yes		Yes		Yes	
Propensity score		Yes		Yes		Yes
Observations	2049	1653	13789	11067	13780	11063
R-squared	0.113	0.136	0.285	0.291	0.186	0.222

Notes: The different dependent variables used are the share of high-skilled workers (measured by the share of workers with a five-year university degree), total employment (measured by the number of effective working hours), and average wages (all in logs). Foreign is a dummy variable for foreign ownership (equal to one if the firm is foreign owned by more than 50 percent and zero otherwise). Time-varying controls include firm-specific productivity, productivity growth, average wage (not in columns (5) and (6)), and capital intensity (all with a two-year lag). For details on the propensity score reweighting estimator see the text. Robust standard errors (in parentheses) are clustered at the firm level. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

A.3.2 Worker training

In Panel B of Table 2 we identify the effect of foreign ownership on worker training without differentiating between different types of training. Here we run the same regressions as in Table 2, but rather than lumping all types of training together, we distinguish between training in engineering, IT, language, marketing, and other (a residual category for all training expenditures not falling into any of the other four categories). In the interest of space, we report the results of three different specifications. Models A, B, and C in Table A.5 correspond, respectively, to columns (2), (4), and (5) in Panel B of Table 2. Model A is based on the largest number of observations, and includes only firm fixed effects and industry-year fixed effects. Model B features the lowest number of observations as we add the lead and contemporaneous foreign ownership dummy along with a set of time-varying firm-level controls (lagged by two years). Model C uses the propensity score weighting estimator described in the main text.

Table A.5: The effect of foreign ownership by type of training

	Worker training				
MODEL A	Engineering	IT	Marketing	Language	Other
Lag foreign	0.477**	0.444**	0.373*	0.630**	0.634***
	(0.221)	(0.208)	(0.192)	(0.289)	(0.212)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes
Time-varying controls					
Propensity score					
Observations	17487	17486	17488	17486	17494
R-squared	0.365	0.329	0.226	0.338	0.452

	Worker training				
MODEL B	Engineering	IT	Marketing	Language	Other
Lag foreign	0.279	0.199	0.269	0.191	0.235
	(0.206)	(0.195)	(0.182)	(0.269)	(0.174)
Foreign	0.0781	0.159	0.126	0.300	0.224
	(0.148)	(0.147)	(0.129)	(0.193)	(0.143)
Forward foreign	-0.159	-0.266	-0.197	-0.119	-0.126
	(0.225)	(0.216)	(0.233)	(0.240)	(0.195)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes
Time-varying controls	Yes	Yes	Yes	Yes	Yes
Propensity score					
Observations	11508	11508	11508	11507	11512
R-squared	0.377	0.343	0.236	0.344	0.455

	Worker training				
MODEL C	Engineering	IT	Marketing	Language	Other
Lag foreign	0.621*	0.540***	0.682***	0.980**	0.741***
	(0.323)	(0.200)	(0.249)	(0.439)	(0.243)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes
Time-varying controls					
Propensity score	Yes	Yes	Yes	Yes	Yes
Observations	13358	13358	13357	13358	13360
R-squared	0.524	0.478	0.340	0.496	0.593

Notes: The dependent variable in all columns is our measure of the stock of knowledge defined as $\tau_{it} = \sum_{j=t_0}^{t} \tau_{ij}$, where τ_{ij} is a 0/1 indicator variable for positive expenditures on worker training (in the specific training category indicated). Foreign is a dummy variable for foreign ownership (equal to one if the firm is foreign owned by more than 50 percent and zero otherwise). Time-varying controls include firm-specific productivity, productivity growth, average wage, and capital intensity (all with a two-year lag). For details on the propensity score reweighting estimator see the text. Robust standard errors (in parentheses) are clustered at the firm level. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

A.4 The market size effect by type of training

In Panel B of Table 5 we identify the market size effect on worker training without differentiating between different types of training. Here we use the information whether firms export through the foreign parent to run the same regressions as in Table 5, but we now distinguish between different types of training. Models A and B in Table A.6 correspond, respectively, to columns (5) and (6) in Panel B of Table 5.

Table A.6: The market size effect by type of training

	Worker training				
MODEL A	Engineering	IT	Marketing	Language	Other
Export via foreign parent	1.086*	0.835*	0.531	0.967*	0.371
	(0.584)	(0.488)	(0.433)	(0.573)	(0.462)
Lag foreign	-0.135	0.156	0.399	0.0717	-0.203
	(0.726)	(0.541)	(0.498)	(0.804)	(0.562)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes
Time-varying controls	Yes	Yes	Yes	Yes	Yes
Propensity score					
Observations	1823	1823	1824	1822	1826
R-squared	0.489	0.436	0.323	0.451	0.550

	Worker training				
MODEL B	Engineering	IT	Marketing	Language	Other
Export via foreign parent	1.114***	0.550	0.547**	0.891**	0.138
	(0.359)	(0.382)	(0.246)	(0.442)	(0.347)
Lag foreign	0.313	0.283	0.833**	0.210	-0.186
	(0.562)	(0.482)	(0.375)	(0.698)	(0.434)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes
Time-varying controls					
Propensity score	Yes	Yes	Yes	Yes	Yes
Observations	2299	2299	2299	2298	2303
R-squared	0.561	0.500	0.364	0.520	0.601

Notes: The dependent variable in all columns is our measure of the stock of knowledge defined as $\tau_{it} = \sum_{j=t_0}^{t} \tau_{ij}$, where τ_{ij} is a 0/1 indicator variable for positive expenditures on worker training (in the specific training category indicated). Foreign is a dummy variable for foreign ownership (equal to one if the firm is foreign owned by more than 50 percent and zero otherwise). Export via foreign parent is a dummy variable indicating whether the firm uses the foreign parent as a distribution channel to access foreign markets. Time-varying controls include firm-specific productivity, productivity growth, average wage, and capital intensity (all with a two-year lag). For details on the propensity score reweighting estimator see the text. Robust standard errors (in parentheses) are clustered at the firm level. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

A.5 Regression results corresponding to Section 4.2.2

A.5.1 Technology transfer

In Panels A and B of Table 5 we identify the market size effect on the hiring of recent university graduates and on worker training, respectively. Columns (5) and (6) in each table use a specific variable—export via foreign parent—to look into the role of the foreign parent in providing access to the export market and thus prompting the acquired firm to engage in skill upgrading. As discussed in Section 4.2.2, another channel through which foreign ownership could lead to skill upgrading is technology transfer from the foreign parent to the acquired firm. In Table A.7 we augment the specifications in columns (5) and (6) of Table 5 using a 0/1 indicator variable for assimilation of foreign technology available in the ESEE data every four years. The estimation results suggest that technology transfers cannot explain skill upgrading in foreign-acquired firms.

Table A.7: The effect of technology transfer on hiring and training

	Hires of graduates		Worker training	
	(1)	(2)	(3)	(4)
Export via foreign parent	1.013**	0.654	0.918**	0.579
	(0.486)	(0.439)	(0.433)	(0.403)
Lag foreign	0.604	0.159	0.677	0.482
	(0.635)	(0.509)	(0.523)	(0.651)
Assimilation of foreign technologies	-0.189	-0.308*	-0.371*	-0.466**
	(0.193)	(0.176)	(0.213)	(0.221)
Assimilation of foreign technologies × Lag foreign	0.406	0.0542	-0.0118	0.0148
	(0.759)	(0.511)	(0.786)	(1.014)
Firm fixed effects	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes
Time-varying controls	Yes		Yes	
Propensity score		Yes		Yes
Observations	1830	2299	1822	2290
R-squared	0.497	0.551	0.643	0.706

Notes: The dependent variable in columns (1) and (2) is our measure of the stock of high-skilled workers defined as $h_{it} = \sum_{j=t_0}^{t} h_{ij}$, where h_{ij} is a 0/1 indicator variable for hires of recent university graduates. In columns (3) and (4) the dependent variable is our measure of the stock of knowledge defined as $\tau_{it} = \sum_{j=t_0}^{t} \tau_{ij}$, where τ_{ij} is a 0/1 indicator variable for positive expenditures on worker training (regardless of the training category). Foreign is a dummy variable for foreign ownership (equal to one if the firm is foreign owned by more than 50 percent and zero otherwise). Export via foreign parent and assimilation of foreign technologies are dummy variables indicating whether the firm carried out the respective activity in a given year. Time-varying controls include firm-specific productivity, productivity growth, average wage, and capital intensity (all with a two-year lag). For details on the propensity score reweighting estimator see the text. Robust standard errors (in parentheses) are clustered at the firm level. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

A.5.2 Financial constraints

In this section we investigate an alternative mechanism that could explain skill upgrading following acquisition, namely that the foreign parent facilitates access to financial resources leading to skill investments. We test this alternative mechanism in two ways. First, we investigate whether key financial variables evolve differently in foreign-acquired firms. Following an extensive literature studying the importance of credit constraints for firm-level investment decisions, we consider three different variables characterizing the financial situation of the firm: (*i*) debt share, i.e. total debt over total assets; (*ii*) debt maturity, defined as the ratio of short-term debt maturing within a year over total debt; and (*iii*) debt service ratio, defined as the sum of debt and interest payments over total sales. Secondly, we investigate whether the effect of foreign acquisitions on skill upgrading depends on the financial situation of the firm at the time of the acquisition. If the credit channel is a relevant mechanism in the context of our analysis, then we should see a stronger effect on skill upgrading in those foreign-acquired firms that are more likely to be credit constrained just before the acquisition.

Table A.8 shows that there is no robust evidence for a differential change in foreign-acquired firms in any of the three financial variables mentioned above. The lack of evidence for changes in key financial figures is not surprising in light of the fact that foreign multinationals do 'cherry-picking': they acquire top-performing firms that are unlikely to be credit constrained. Table A.8 shows that the effects of foreign acquisitions on skill upgrading are not significantly related to the financial situation of the firm just before the acquisition. In particular, the coefficients of the interaction terms between foreign ownership and our firm-level financial measures (debt share, debt maturity, and debt service ratio) are all equal to zero (in a statistical sense), for both hiring and training.[40] Overall, we find no evidence for the credit channel to explain skill upgrading in foreign-acquired firms.

[40]The financial variables enter these regressions with two lags in order to measure the financial situation of the firm one year before the acquisition.

Table A.8: The effect of foreign ownership on financial constraints

	Debt share		Debt maturity		Debt service ratio	
	(1)	(2)	(3)	(4)	(5)	(6)
Lag foreign	0.00655	0.0337	0.0198	0.0386	-0.0385	-0.0082
	(0.0247)	(0.0325)	(0.0218)	(0.0273)	(0.0438)	(0.0350)
Foreign	0.0126		0.0138		-0.0881*	
	(0.0215)		(0.0244)		(0.0471)	
Forward foreign	-0.0157		0.00664		0.0255	
	(0.0219)		(0.0237)		(0.0686)	
Observations	11195	13709	11500	14190	11479	13115
R-squared	0.047	0.057	0.066	0.072	0.050	0.043
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time-varying controls	Yes		Yes		Yes	
Propensity score		Yes		Yes		Yes

Notes: The dependent variable in columns (1)-(2) is debt share (defined as total debt over total assets), in columns (3)-(4) debt maturity (defined as the ratio of short-term debt over total debt) and in columns (5)-(6) debt service ratio (defined as the sum of debt and interest payments over total sales). Foreign is a dummy variable for foreign ownership (equal to one if the firm is foreign owned by more than 50 percent and zero otherwise). Time-varying controls include firm-specific productivity, productivity growth, average wage, and capital intensity (all with a two-year lag). For details on the propensity score reweighting estimator see the text. Robust standard errors (in parentheses) are clustered at the firm level. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

Table A.9: Financial constraints, foreign ownership, hiring and training

	Hires of recent university graduates					
	Debt share		Debt maturity		Debt service ratio	
Panel A	(1)	(2)	(3)	(4)	(5)	(6)
Lag foreign	0.339	-0.0043	0.458	0.185	0.230	0.218
	(0.318)	(0.336)	(0.535)	(0.495)	(0.247)	(0.198)
Foreign	0.139		0.149		0.194	
	(0.125)		(0.117)		(0.140)	
Forward foreign	-0.0594		-0.0734		-0.0829	
	(0.167)		(0.170)		(0.168)	
2 Lag financial var.	0.354**	0.117	-0.139	-0.0307	0.0356	0.0320
	(0.139)	(0.177)	(0.0917)	(0.112)	(0.0289)	(0.0315)
Lag foreign × 2 Lag financial var.	-0.226	0.638	-0.297	0.190	-0.124	0.119
	(0.501)	(0.592)	(0.646)	(0.599)	(0.199)	(0.175)
Observations	10297	11197	10492	11458	9578	9566
R-squared	0.368	0.412	0.367	0.411	0.357	0.406
	Worker training					
	Debt share		Debt maturity		Debt service ratio	
Panel B	(1)	(2)	(3)	(4)	(5)	(6)
Lag foreign	0.534	1.059	0.503	0.386	0.375*	0.985***
	(0.397)	(0.666)	(0.916)	(1.192)	(0.215)	(0.308)
Foreign	0.270*		0.246		0.298*	
	(0.156)		(0.150)		(0.160)	
Forward foreign	0.0914		0.0642		0.0783	
	(0.198)		(0.205)		(0.185)	
2 Lag financial var.	0.372	-0.100	-0.126	-0.0530	-0.0966*	-0.0782
	(0.230)	(0.274)	(0.144)	(0.187)	(0.0519)	(0.0520)
Lag foreign × 2 Lag financial var.	-0.350	-0.401	-0.191	0.558	-0.101	-0.424
	(0.782)	(1.383)	(1.010)	(1.241)	(0.188)	(0.261)
Observations	10289	11193	10484	11454	9578	9566
R-squared	0.540	0.687	0.536	0.687	0.542	0.687
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time-varying controls	Yes		Yes		Yes	
Propensity score		Yes		Yes		Yes

Notes: In Panel A the dependent variable in all columns is our measure of the stock of high-skilled workers defined as $h_{it} = \sum_{j=t_0}^{t} h_{ij}$, where h_{ij} is a 0/1 indicator variable for hires of recent university graduates. In Panel B the dependent variable in all columns is our measure of the stock of knowledge defined as $\tau_{it} = \sum_{j=t_0}^{t} \tau_{ij}$, where τ_{ij} is a 0/1 indicator variable for positive expenditures on worker training (regardless of the training category). Foreign is a dummy variable for foreign ownership (equal to one if the firm is foreign owned by more than 50 percent and zero otherwise). The financial variable in columns (1)-(2) is debt share (defined as total debt over total assets), in columns (3)-(4) debt maturity (defined as the ratio of short-term debt over total debt) and in columns (5)-(6) debt service ratio (defined as the sum of debt and interest payments over total sales). Time-varying controls include firm-specific productivity, productivity growth, average wage, and capital intensity (all with a two-year lag). For details on the propensity score reweighting estimator see the text. Robust standard errors (in parentheses) are clustered at the firm level. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

A.6 Further results on the output and productivity effects

In Table 6 we investigate the complementarity between innovation and skill upgrading and how both activities jointly affect firm output. For given levels of technology and skills, i.e. for given values of λ, z, and τ, output in our model is of course an increasing function of total employment. To isolate the productivity effects from this scale effect we include labor as an additional control variable in the estimation. The results in columns (1) and (2) of Table A.11 indicate that this does not reduce the significance of the interaction terms between innovation and (the two different forms of) skill upgrading.

We next use the estimation routine developed by Olley and Pakes (1996) to estimate total factor productivity (TFP) at the firm level. This standard measure of TFP controls for firm selection (market exit), unobserved firm heterogeneity, and endogeneity of inputs. The results are presented in Table A.10, where we follow exactly the same strategy as in Table 6, but replace output by TFP as the dependent variable. Similar to the results in the main text, we find evidence that both hiring and worker training increase firm productivity, since both variables enter the regression with a positive and highly significant coefficient in columns (4) and (6). In columns (5) and (7) we interact the two variables with process innovation. These regressions reveal that the productivity gains are largest in firms with a high technology level as the respective coefficients for the interaction terms are highly significant and positive.

As a final robustness check, we relax the assumption of strict exogeneity for our technology and skill variables by using a fixed-effects IV strategy. We treat these variables and the respective interaction terms as predetermined variables and instrument them with their first and second lags. The results for output and TFP as the dependent variables are, respectively, presented in columns (3)-(4) and (5)-(6) of Table A.11. In both estimations, the interaction terms between technology upgrading and skill upgrading are positive and highly significant. We obtain almost identical results (not reported) when we treat the variables as endogenous and instrument them with their second lags only.

Table A.10: The productivity effects of skill upgrading and process innovation

	TFP (in logs)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Lag foreign	0.0869*	0.0670	0.0943	0.0390	0.0353	0.0362	0.0294
	(0.0447)	(0.0480)	(0.0613)	(0.0473)	(0.0468)	(0.0486)	(0.0481)
Process innovation				0.200***	0.153***	0.225***	0.163***
				(0.0234)	(0.0272)	(0.0258)	(0.0320)
Hiring				0.165***	0.0550		
				(0.0317)	(0.0394)		
Hiring × Process innovation					0.0639***		
					(0.0177)		
Training						0.104***	0.0370
						(0.0192)	(0.0243)
Training × Process innovation							0.0517***
							(0.0145)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-varying controls		Yes		Yes	Yes	Yes	Yes
Propensity score			Yes				
Observations	19505	16389	14904	16389	16389	15232	15232
R-squared	0.265	0.284	0.268	0.308	0.311	0.318	0.320

Notes: The dependent variable in all columns is the firm-specific total factor productivity (in logs) estimated with the Olley and Pakes (1996) estimation routine. Foreign is a dummy variable for foreign ownership (equal to one if the firm is foreign owned by more than 50 percent and zero otherwise). Process innovation ($\ln[1+\rho_{it}]$) is a measure of the technology level of the firm with $\rho_{it} = \sum_{j=t_0}^{t} \rho_{ij}$, where ρ_{ij} is a 0/1 indicator for process innovation. Hiring ($\ln[1+h_{it}]$) is a measure of the stock of high-skilled workers with $h_{it} = \sum_{j=t_0}^{t} h_{ij}$, where h_{ij} is a 0/1 indicator variable for hires of recent university graduates. Training ($\ln[1+\tau_{it}]$) is a measure of the stock of knowledge with $\tau_{it} = \sum_{j=t_0}^{t} \tau_{ij}$, where τ_{ij} is a 0/1 indicator variable for positive expenditures on worker training (regardless of the training category). Time-varying controls include average wage and capital intensity (all with a two-year lag). For details on the propensity score reweighting estimator see the text. Robust standard errors (in parentheses) are clustered at the firm level. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.

Table A.11: The output and productivity effects of skill upgrading and process innovation - Robustness

	Output (in logs)		Output (in logs)		TFP (in logs)	
	(1)	(2)	(3)	(4)	(5)	(6)
	FE	FE	FE-IV	FE-IV	FE-IV	FE-IV
Lag foreign	0.0649*	0.0443	0.0773	0.106**	0.0369	0.0746*
	(0.0367)	(0.0371)	(0.0547)	(0.0534)	(0.0467)	(0.0445)
Process innovation	0.0467**	0.0416*	0.157***	0.205***	0.143***	0.150***
	(0.0203)	(0.0232)	(0.0345)	(0.0488)	(0.0337)	(0.0466)
Hiring	0.0197		0.0181		0.0183	
	(0.0353)		(0.0520)		(0.0460)	
Hiring × Process innovation	0.0407***		0.0838***		0.0742***	
	(0.0154)		(0.0222)		(0.0195)	
Training		0.0116		0.0330		0.0183
		(0.0198)		(0.0347)		(0.0307)
Training × Process innovation		0.0368***		0.0542***		0.0607***
		(0.0111)		(0.0191)		(0.0170)
Labor	0.834***	0.837***				
	(0.0251)	(0.0262)				
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time-varying controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16449	15286	16224	12812	16131	12756
R-squared	0.559	0.563	0.285	0.320	0.310	0.342
Hansen J (p-val.)	n.a.	n.a.	0.525	0.991	0.652	0.634

Notes: The dependent variable in columns (1) to (4) is firm-specific output (in logs) expressed in 2006 prices using firm-level price indexes. The dependent variable in columns (5) and (6) is the firm-specific total factor productivity (in logs) estimated with the Olley and Pakes (1996) estimation routine. Foreign is a dummy variable for foreign ownership (equal to one if the firm is foreign owned by more than 50 percent and zero otherwise). Process innovation ($\ln[1+\rho_{it}]$) is a measure of the technology level of the firm with $\rho_{it} = \sum_{j=t_0}^{t} \rho_{ij}$, where ρ_{ij} is a 0/1 indicator for process innovation. Hiring ($\ln[1+h_{it}]$) is a measure of the stock of high-skilled workers with $h_{it} = \sum_{j=t_0}^{t} h_{ij}$, where h_{ij} is a 0/1 indicator variable for hires of recent university graduates. Training ($\ln[1+\tau_{it}]$) is a measure of the stock of knowledge with $\tau_{it} = \sum_{j=t_0}^{t} \tau_{ij}$, where τ_{ij} is a 0/1 indicator variable for positive expenditures on worker training (regardless of the training category). Employment (in logs) are effective hours worked. Time-varying controls include average wage and capital intensity (all with a two-year lag). Robust standard errors (in parentheses) are clustered at the firm level. *,**,*** denote significance at the 10%, 5%, 1% levels, respectively.