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Imported Inputs and Skill Upgrading

*Rosario Crinò**

* University of Brescia, Centro Studi Luca d'Agliano and IAE-CSIC

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Rosario Crinò†

University of Brescia, LdA, and IAE-CSIC

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Abstract

This paper studies the effect of imported inputs on relative skilled labor demand. To this purpose, it uses firm-level data for 27 transition countries and propensity score matching techniques. The results show that importing inputs induces skill upgrading: according to a conservative estimate, it explains roughly one-quarter of the higher share of skilled employment observed at importers. The paper discusses possible mechanisms behind this result. In particular, it reports suggestive evidence that importing may lead firms to engage in skill-intensive activities, such as production of new goods, improvements in product quality and, to a lesser extent, R&D and technology adoption.

JEL Numbers: F1.

Keywords: Imported Inputs; Relative Skilled Labor Demand; Firm-Level Data; Transition Countries; Propensity Score Matching.

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†Address: University of Brescia, Department of Economics. Via S. Faustino 74/B, 25122 Brescia (Italy). E-mail: rosario.crino@eco.unibs.it.

1 Introduction

Understanding how imported intermediates affect the performance of firms is an important goal for policy makers in many industrializing countries (see, e.g., Mohan, 2008). It is also the objective of a growing number of studies based on firm-level data. These studies document substantial productivity gains from importing, due to a combination of variety, quality, and learning effects.[1] They also show that imported inputs induce first-order changes in firms' activities, such as production of new goods, improvements in product quality, and new investment in R&D aimed at adopting the foreign technologies embodied in these inputs.[2] More limited and ambiguous is instead the evidence on how imported inputs affect the relative demand for skilled labor.[3] The existing firm-level studies find positive effects in Mexico (Harrison and Hanson, 1999), Brazil (Fajnzylber and Fernandes, 2009), and Turkey (Morrison Paul and Yasar, 2009; Meschi et al., 2011), no effect in Chile (Pavcnik, 2003), and negative effects in China (Fajnzylber and Fernandes, 2009). The aim of this paper is to provide novel firm-level evidence on how imported inputs affect the relative demand for skilled labor in the industrializing countries.[4]

My analysis rests on a large sample of firms operating in 27 transition countries in Central-Eastern Europe and Central Asia. As illustrated in Section 2, the data comes from two surveys, conducted by the World Bank and the European Bank for Reconstruction and Development in 2002 and 2005. For the purpose of this paper, these surveys have two notable features. The first is that the countries they encompass represent an interesting case study, for a number of reasons: (i) they are relatively understudied in the ongoing debate on trade and relative skilled labor demand;[5] (ii) over recent decades, they have become increasingly integrated in world markets and have experienced a simultaneous shift in labor demand towards more skilled workers;[6] (iii) their firms rely substantially

[1] See, in particular, Schor (2004), Amiti and Konings (2007), Yasar and Morrison Paul (2007), Kasahara and Rodrigue (2008), Kasahara and Lapham (2009), Sivadasan (2009), Altomonte and Békés (2010), Halpern et al. (2011), and Khandelwal and Topalova (2011). See Muendler (2004) for a relevant exception.

[2] See Goldberg et al. (2010a,b) on production of new goods, Verhoogen (2008) and Kugler and Verhoogen (2009, 2011) on output and input quality, and Keller (2004) on technology adoption.

[3] On this point, see the extensive and detailed discussion in Goldberg and Pavcnik (2007).

[4] A parallel literature analyzes the effects of imported inputs in industrialized economies. In that literature, imported inputs are often taken as a proxy for offshoring. Studies on productivity effects include Amiti and Wei (2009) and Hijzen et al. (2010). As for labor demand effects, industry-level studies include Feenstra and Hanson (1999), Hijzen et al. (2005), and Crinò (2010b, 2011), whereas firm-level studies include Görg and Hanley (2005), Biscourp and Kramarz (2007), and Becker et al. (2009). Updated surveys of this literature can be found in Feenstra and Hanson (2003), Hijzen (2005), Crinò (2009), and Feenstra (2010).

[5] See Epifani and Gancia (2006, 2008) for two recent contributions to this debate.

[6] For a description of these trends, see Aghion and Commander (1999) and Commander and Kollo (2008).

on foreign inputs.[7] The second important feature of the surveys is that they offer cross-country comparable information on many firm characteristics. In particular, besides containing detailed data on firms' importing activities and skill composition of employment, they allow constructing a comprehensive set of covariates that control for many other attributes of the firms: structural characteristics (e.g., size, age, productivity, and capital intensity), trade and ownership status, use of Information and Communication Technologies (ICT), competition and business environment, and relative skilled labor supply.

I use Propensity Score Matching (PSM) to study how imported inputs affect the relative demand for skilled labor in these firms. Specifically, as explained in Section 3, my empirical strategy consists of estimating the effect of importing (the *treatment*) on the firm's skilled labor share of employment (the *outcome*).[8] To yield unbiased estimates PSM requires that, after controlling for observable characteristics, no other factor is left that influences treatment assignment and is also correlated with the outcome.[9] Hence, I match the importers with a subsample of non-importers, selected to be similar in terms of my large set of covariates. To quantify the effect of importing, I then calculate the average difference in the share of skilled employment between the two types of matched firms (Average Treatment effect on the Treated, ATT).

My empirical approach is different from the standard one used in the literature, which is based on OLS estimation of linear models for relative skilled labor demand. In particular, PSM has two advantages. First, it does not require parametric assumptions and, second, it allows conditioning on a larger set of covariates. Nevertheless, the estimates obtained with PSM may be less efficient than OLS estimates (provided that the parametric model is correctly specified), because PSM discards the non-matched observations. For comparison, I therefore also show OLS estimates of linear models, controlling for the same covariates used in PSM. Moreover, PSM estimates may be sensitive to the

[7] In my sample, 29% of firms purchase inputs from abroad. Imported inputs account for 54% of their total expenditure in intermediates.

[8] For any given, elastic relative supply of skilled labor, a higher relative demand at importers would imply a greater share of skilled employment in these firms compared to non-importers. Following the literature, I use the term 'skill upgrading' to indicate a higher relative demand for skilled labor (see, e.g., Pavcnik, 2003). In order to be more confident that my estimates are indeed isolating differences in relative demand between importers and non-importers, in the empirical analysis I control also for a number of firm-level proxies for relative skilled labor supply.

[9] Instead, factors that influence the treatment without affecting the outcome would not cause bias. An example of such factors is differences in transportation technologies (and thus costs) across firms. These differences may explain why firms fall into either the importer or the non-importer category, without necessarily having an independent effect on relative skilled labor demand. Other factors that may create heterogeneity in import status without affecting labor demand are cross-firm differences in the fixed costs of importing from foreign locations (see Kasahara and Lapham, 2009, for a theoretical treatment).

matching estimator and the estimation sample. I address both issues through a large number of robustness checks.

Thanks to the use of a rich and high-quality data set, my covariates plausibly exhaust all observable firm characteristics associated with import status and relative skilled employment. However, the selection of firms into importing and the skill composition of their workforce could be jointly influenced also by unobservable characteristics. If this was the case, my estimates would still be biased.[10] To verify the robustness of the baseline estimates with respect to this 'selection on unobservables', I use two sensitivity analyses proposed by Rosenbaum (2002) and Ichino et al. (2008). The basic idea is to assess whether the estimates would be substantially changed, or even overturned, by unobservable factors correlated with outcome and treatment. In the literature on trade and labor markets, few studies have so far combined PSM with similar sensitivity analyses. The present paper builds on previous work by Becker and Muendler (2008), which provides one of the first applications of these methodologies to the trade-and-labor literature.[11] In addition to the sensitivity analyses, I also take advantage of a subsample of firms interviewed in both periods and estimate panel regressions controlling for firm fixed effects.

The results are discussed in Section 4. They show that importing inputs induces skill upgrading, and that the effect is non-negligible. A conservative estimate implies, in fact, that importing raises the employment share of skilled labor by about 3 percentage points. The share of skilled employment of importers is 11 percentage points higher than that of non-importers, so importing explains roughly 25% of the difference between the two types of firms. The baseline estimates are substantiated by a large number of robustness checks and extensions, which allow for different matching estimators, different estimation samples, different definitions of importers and skills, and cross-country heterogeneity in the ATT. They are also largely insensitive to selection on unobservables, as suggested by the sensitivity analyses and the panel regressions.

I devote Section 5 to discuss possible mechanisms behind these results, and to connect my analysis with other strands of research on imported intermediates. First, I consider that foreign inputs may induce skill upgrading by leading firms to engage in skill-intensive activities. I report suggestive evidence that is broadly consistent with this mechanism. In particular, building on the

[10] Indeed, in some previous studies, unobserved heterogeneity completely determines the positive effect of importing estimated by OLS (Pavcnik, 2003).

[11] Another example of work following that study is Crinò (2010a).

received literature and taking advantage of the richness of the data, I find that importers are more likely than non-importers to engage in activities such as production of new goods (Goldberg et al., 2010a,b), improvements in product quality (Verhoogen, 2008; Kugler and Verhoogen, 2009, 2011), and R&D/technology adoption (Keller, 2004). I also find these activities (especially the first two) to be associated with higher relative skilled employment within the firm. Second, I consider that imported inputs may induce skill upgrading by substituting for unskill-intensive stages of production (Feenstra and Hanson, 1999). To have a sense of the empirical relevance of this mechanism for my sample countries, I compare their skill abundance with that of their main providers of foreign inputs. The results of this exercise are largely inconsistent with this second explanation. I conclude by discussing the implications of my findings in Section 6.

2 Data and Preliminary Evidence

2.1 Data

The data comes from the 2002 and 2005 issues of the 'World Bank Enterprise Surveys' (WBES), a joint initiative of the World Bank Group and the European Bank for Reconstruction and Development.[12] The WBES cover manufacturing and services firms from 27 transition countries in Central-Eastern Europe and Central Asia (overall, 6667 firms in 2002 and 7942 in 2005). The surveys are comparable across countries, due to the adoption of identical questionnaires and the same stratified random sampling scheme.[13] Some of the firms (1426) are interviewed in both waves of the WBES: in Sections 4.2 and 4.3, I exploit this panel component of the data to test the robustness of the results obtained on the pooled sample of firms.[14]

Compared to other data sets, the WBES have a distinguishing feature: they contain uniquely

[12] The WBES exist also for the years 1999 and 2009. However, the 1999 issue has very limited information on importing, whereas the 2009 survey is not comparable with earlier ones due to main differences in the questionnaires. Hence, following Correa et al. (2010) and Gorodnichenko et al. (2010), the analysis in this paper is based only on the 2002 and 2005 waves.

[13] The sectorial composition of the samples is determined according to the contribution of manufacturing and services sectors to each country's GDP. Firms operating in industries subject to price regulations and prudential supervision by governments (e.g., banking, electricity, water, and rail transport) are not included in the surveys. In the remaining industries, firms with just one or more than 10000 employees are not sampled.

[14] The small size of the panel is not due to firm exit, as the average exit rate is only 8%. It is rather due to low completion of the 2005 survey by firms that participated in the 2002 wave and were selected to be reinterviewed (only 30% of the selected firms completed the 2005 wave). The low completion rate, in turn, is mostly due to the refusal of these firms to participate in the new wave (35% of the non-respondents) and to the impossibility of reaching the eligible respondents within these firms (25%).

rich information on an unusually large number of firm characteristics. This rich content is crucial, for at least three reasons. First, the surveys report detailed information on firms' importing activities, which I can use to construct the treatment indicators. Second, they report information on the educational and occupational composition of firms' workforce, which I can use to construct the outcome variables.[15] Third, the WBES allow constructing a large number of covariates that proxy for other firm characteristics. These characteristics are possibly correlated with firms' import status and relative skilled employment, and may thus bias the treatment effect if not adequately controlled for. In what follows, I describe the main variables used in the empirical analysis; their names, definitions, and descriptive statistics are provided in Table A3.

2.2 Variables

2.2.1 Treatment and Outcome

The WBES ask firms to report: (1) whether they purchase inputs from abroad, (2) the import share of their total expenditure in intermediates, and (3) the fraction of inputs imported directly as opposed through domestic distributors. In most of the paper, I define importers as firms purchasing any share of their inputs directly from abroad. The *treatment* indicator is therefore a dummy equal to 1 for these firms. To proxy for relative skilled labor demand, I use information on the educational composition of firms' workforce. In particular, the *outcome* variable is the employment share of workers with some university or higher education in the firm.[16]

2.2.2 Covariates

The covariates summarize four groups of firm characteristics, which may jointly affect import status and relative skilled employment.[17] (1) *Structural characteristics, trade status, and use of ICT.* These variables control for firm size, age, capacity utilization, changes in labor productivity and capital intensity, export status, and use of ICT (internet and E-mail) to interact with clients and suppliers. (2) *Ownership status.* These variables control for whether the firm is state owned, privatized, or foreign participated. (3) *Competition, market, and business environment.* These

[15] Instead, the WBES do not contain information on wages.

[16] In Section 4.2, I use alternative definitions of outcome and treatment for robustness.

[17] Whenever possible, the covariates are measured three years before the survey. Instead, treatment and outcome always refer to the survey period. See Table A3 for details.

variables control for whether the firm competes on the national market, faces import competition, is credit constrained, has the government or multinationals among its customers, and receives subsidies from the national or local governments. (4) *Relative labor supply.* These variables control for differences in relative skilled labor supply across firms: they include an indicator for whether the firm has problems in finding the necessary skills, and the number of weeks it spent to fill out the most recent vacancies for white-collar and blue-collar jobs.[18]

2.3 Preliminary Evidence

Table 1 reports the total number of firms, the number of importers and their import share. Almost all firms (14008) answer the questions on importing and so enter the sample used in this paper. Roughly 29% of them have positive imports, and foreign inputs account for 54% of their total expenditure in intermediates. Across countries, the share of importers ranges between 16% (Uzbekistan) and 56% (Albania), whereas the import share goes from 37% (Turkey) to 68% (Georgia). Overall, these figures suggest importing inputs to be a widespread and relevant practice in the 27 transition countries.[19]

Table 2 reports the main provider of foreign inputs for each sample country. The main providers are identified using bilateral data on trade in intermediates, available from Feenstra et al. (2005) for the year 2000. For each country and trading partner, the table also shows proxies for economic development (per capita income) and for the abundance of production factors (skilled labor and capital).[20] Note that the main providers account for a substantial share (15 to 50%) of total

[18] To isolate shifts in relative labor demand, most studies estimate a specification for the skilled labor share of wage bill, controlling for the relative wage of skilled workers (see, in particular, Feenstra and Hanson, 1999). This approach is unfeasible in my case, because no information on wages is available in the WBES. Instead, I condition estimation on these three variables, which capture differences in relative labor supply between importers and non-importers. I can then be more confident that a greater share of skilled employment in the former firms does indeed reflect a higher relative demand for skilled labor (rather than a higher relative supply at given demand). Moreover, I always use these variables in conjunction with country-industry-year dummies, so that identification is driven by variation across firms within the same country, industry, and time period: the assumption of equal relative supply may be more credible in such homogeneous groups of firms.

[19] These figures are broadly consistent with those for other industrializing countries and small open economies. For instance, the share of importers is roughly 25% in Chile (Pavcnik, 2003; Kasahara and Lapham, 2009), 20% both in Indonesia (Amiti and Konings, 2007) and in Belgium (Muuls and Pisu, 2007), and 27% in Sweden (Anderson et al., 2008). Moreover, these figures imply that imported inputs account for roughly 16% ($0.29 \cdot 0.54 = 0.16$) of an industry's total expenditure in intermediates, slightly less than the corresponding value (19%) for the EU (Crinò, 2011). Figures for the U.S. are instead lower: (i) the share of importers is 2% in total firms (Bernard et al., 2009) and 14% in manufacturing firms (Bernard et al., 2007); (ii) across industries, imported inputs account for roughly 12% of the average expenditure in intermediates (Crinò, 2009).

[20] Per capita income is sourced from the Penn World Tables. Skill abundance is the share of population with complete tertiary schooling, sourced from Barro and Lee (2010). Capital abundance is the capital stock per worker,

imported inputs across the 27 countries, and that they are generally richer and better endowed economies from the EU.[21]

Table 3 reports summary statistics on outcome and covariates, separately for importers (panel a)) and non-importers (panel b)). For each variable, the table also shows the simple and conditional mean difference between the two types of firms (panels c) and d), respectively).[22] Note that importers employ more skilled labor than non-importers as a share of total employment: the mean difference is 11 percentage points (p.p.), or 21%, and is highly significant (t-statistic greater than 20).[23] Note also, however, that importers differ from non-importers along other dimensions. In particular they are larger, older, more productive and more capital-intensive, more likely to export, to be foreign owned, to use ICT, to compete on the national market, to face import competition, and to have the government or foreign multinationals among their clients. At the same time, importers are less likely to be state owned and credit constrained, and exhibit a lower rate of capacity utilization. Interestingly, importers also face more difficulties in finding the necessary skills, and require relatively more time to fill out a white-collar than a blue-collar vacancy.[24]

Differences in observable characteristics may jointly influence the selection of firms into importing and the skill composition of their workforce. The simple comparison of outcomes by import status may thus yield biased estimates of the effect of importing on relative skilled labor demand. Table 4 takes a first step towards controlling for observable firm characteristics, by reporting OLS regressions of the outcome on treatment and covariates. Moving from panel a) to panel d), the set of firm-level controls becomes richer. Besides the covariates, the specifications also include country-industry and year dummies (panels a)-c)) or country-industry-year dummies (panel d)). Note that the coefficient on the importer indicator is always positive, very precisely estimated, and economically large: the point estimates imply that, after controlling for observed characteristics, the share of

computed using investment and population data from the Penn World Tables.

[21] The same conclusions are reached when considering also the second and third main provider of each country. Results available upon request.

[22] Results in panel d) control for: country-industry and year effects in the case of outcome and variables sub 2.1)-2.3); country-industry-year effects in the case of variables sub 2.4).

[23] This figure is broadly consistent with those for other industrializing countries such as Mexico, where importers are 18% more skill-intensive than non-importers (Riano, 2008). It is instead higher than figures for the U.S., where the skill-intensity premium of importers is 6% (Bernard et al., 2007). As for the results on individual countries, the mean difference in outcomes between importers and non-importers is always positive; it is also precisely estimated for 25 out of 27 countries (see Table A1, panel b)).

[24] If anything, this last finding suggests importers to face a lower relative supply of skilled labor.

skilled employment is higher at importers by more than 5 p.p..[25]

OLS regressions like those in Table 4 assume a strict, linear parametric model for the regression function. If the linearity assumption is not accurate, the estimates may be biased and sensitive to even minor changes in the specification (Imbens and Wooldridge, 2009).[26] In the next section, I thus depart from OLS, and use instead PSM to adjust for differences in observable characteristics between importers and non-importers.

3 Methodology

3.1 Propensity Score Matching

Let $i = 1, ..., N$ index firms, and N_T and N_C denote the number of treated (importing) and control (non-importing) firms, so that $N = N_T + N_C$. Also, let IMP denote the treatment status of a firm, i.e., $IMP = 1$ if the firm imports and $IMP = 0$ if it does not. Finally, call ESH_1 and ESH_0 the firm's outcomes (employment shares of skilled labor) if it does and does not import, respectively (Rubin, 1974). My interest lies in obtaining unbiased estimates of the ATT, which measures the average difference between the share of skilled employment actually observed at importers and the share that would have been observed had these firms not imported:

$$
\begin{aligned}
ATT &= E(ESH_1 - ESH_0 | IMP = 1) \\
&= E(ESH_1 | IMP = 1) - E(ESH_0 | IMP = 1).
\end{aligned}
$$

Clearly, $E(ESH_0|IMP = 1)$ is not observed and must be estimated. Using the average outcome across all non-importers would produce biased estimates of the ATT, because other firm characteristics jointly influence import status and relative skilled employment. However, under the following identifying assumptions - jointly known as 'strong ignorability' (Rosenbaum and Rubin, 1983) - $E(ESH_0|IMP = 1)$ can be estimated using the outcomes of a selected subsample of non-importers:

[25] The coefficients on the covariates (available upon request) are often significant and generally have the expected sign. In particular, they suggest the share of skilled employment to be higher in firms that also export, are foreign participated, use ICT, and serve the government or foreign multinationals. As for the results on individual countries, most coefficients on the importer dummy are positive across the four specifications; see Table A1, panels c)-f).

[26] Imbens and Wooldridge (2009) suggest the following rule of thumb for evaluating the reliability of linear regression estimates. They recommend computing the mean difference in each covariate between treated and control units, normalized by the square root of the sum of the two variances. Values greater than one-quarter would cast doubt on linear regression estimates. In my case, the normalized difference exceeds one-quarter for many covariates.

1. *Conditional Independence Assumption* (CIA): $ESH_0 \perp IMP | X$;

2. *Common Support Assumption* (CSA): $\Pr(IMP = 1|X) < 1$.

The CIA states that, conditional on a vector of covariates X, the counterfactual outcome in the absence of treatment is independent of treatment status.[27] In other words, the observed characteristics in X exhaust all factors that jointly affect import status and relative skilled employment. Under the CIA, $E(ESH_0|IMP = 1)$ can be estimated using the average outcome of a subsample of non-importers, which have the same X-vector as the importers. In turn, the CSA ensures that both importers and non-importers exist with the same covariates X.

Following Rosenbaum and Rubin (1983), if the CIA holds conditional on X, then it also holds conditional on the scalar variable $p(X)$ - known as the *propensity score* - which in my case measures the conditional probability of importing given X. Accordingly, instead of matching firms based on the vector X, I match them based on the propensity score $p(X)$. In particular, I first estimate the propensity score by logit. Then, I use nearest-neighbor matching with replacement to pair each importer with the closest non-importer in terms of the estimated $p(X)$.[28] Finally, I compute the ATT as:

$$ATT = \frac{1}{N_T} \sum_{i=1}^{N_T} \left(ESH_i - \frac{1}{N_{C(i)}} \sum_{m(i)=1}^{N_{C(i)}} ESH_{m(i)} \right),$$

where $m(i) = 1, ..., N_{C(i)}$ indexes non-importers matched to the i-th importer.[29] To improve matching quality, I drop importers whose propensity score falls outside the support of the propensity score of non-importers.[30] To perform statistical inference on the ATT, I use both analytical and bootstrapped standard errors (based on 100 replications).[31]

I employ two statistics to check that the distribution of covariates is balanced between importers and matched non-importers.[32] The first statistic is the pseudo-R^2 obtained from logit estimation of

[27] This assumption is also known as 'unconfoundedness' or 'selection on observables'.

[28] In Section 4.2, I use alternative matching estimators for robustness.

[29] $N_{C(i)} = 1$, unless multiple non-importers exist with the same value of the propensity score.

[30] I obtain very similar results (available upon request) if I impose the common support restriction through a different method, namely, by dropping importers matched to non-importers with the lowest propensity score density (using a 0.01 caliper).

[31] There is an ongoing debate on how to estimate the variance of the ATT. See, in particular, Abadie and Imbens (2006).

[32] This 'balancing condition' implies that firms with the same propensity score have the same distribution of observable characteristics independent of their import status ($IMP \perp X | p(X)$). Provided that the CIA and CSA are also verified, import status can then be considered as random.

the propensity score on the matched sample. The second statistic is the standardized bias, which measures the mean difference in each covariate between importers and matched non-importers, as a percentage of the square root of the average variance (Rosenbaum and Rubin, 1985).[33] If matching is successful at balancing the distribution of covariates, both statistics will be small.[34]

3.2 Sensitivity Analyses for Selection on Unobservables

The use of a large and high-quality data set like the WBES makes it plausible that the covariates exhaust all observable firm characteristics correlated with import status and relative skilled employment. Yet, the CIA could fail even in such a rich data environment. This would happen if firms' selection into importing and relative labor demand were jointly influenced also by unobservable characteristics. In particular, any unobservable factor making a firm more likely to import and to use skilled labor (e.g., a positive productivity shock, the adoption of a modern technology, the use of advanced management practices) would bias the baseline ATT upward, leading me to overestimate the effect of importing.

The validity of the CIA cannot be tested using non-experimental data. Some methods exist, however, to assess the sensitivity of the baseline estimates to violations of the CIA. The size of the bias induced by a certain violation depends on the correlation of the unobservable characteristic with treatment and outcome. In a nutshell, the aim of the sensitivity analyses is to assess whether modest deviations from the CIA would substantially change, or even overturn, the baseline ATT. Showing that this is not the case would give further credibility to the baseline estimate.

I now sketch two sensitivity analyses, respectively proposed by Rosenbaum (2002) and Ichino et al. (2008).[35] Both approaches assume the CIA to be violated due to the presence of an unobserved binary characteristic ('confounder') $Z \in \{0, 1\}$. The method proposed by Ichino et al. (2008) assesses the sensitivity of the point estimate of the ATT, with respect to changes in a small set

[33] In particular, for any covariate x, the standardized bias is computed as:

$$SB(x) = \frac{\overline{x}_{1m} - \overline{x}_{0m}}{\sqrt{(1/2)(V_{1m}(x) + V_{0m}(x))}} \cdot 100,$$

where $\overline{x}_{1m}$ and $\overline{x}_{0m}$ are the means of the covariate across importers and matched non-importers, whereas V_{1m} and V_{0m} denote the respective variances. As common in the literature, I report the median value of the standardized bias across all covariates.

[34] Estimation and testing are performed with the Stata routines `psmatch2` and `pstest` (Leuven and Sianesi, 2003).

[35] Comprehensive surveys of this literature can be found in Blundell and Costa Dias (2002), Caliendo and Kopeinig (2008), and Imbens and Wooldridge (2009).

of parameters governing the association of Z with treatment and outcome. Instead, Rosenbaum (2002) assesses the sensitivity of the significance level of the ATT, with respect to changes in a single parameter measuring the correlation of Z with treatment assignment.

3.2.1 Rosenbaum (2002) Bounds

The aim of this sensitivity analysis - known as the 'Rosenbaum bounds' approach - is to assess how strongly a confounder must influence the selection process to undermine inference about the ATT. Suppose that the conditional probability of importing given X is described by $p = \Pr(IMP = 1|X) = F(\beta X + \gamma Z)$, where F is the logistic distribution and γ measures the effect of the confounder on the probability. If Z has no effect, γ is zero and the probability is entirely determined by the covariates. Otherwise, the probability can differ even between two firms with the same observed characteristics.

Take a pair of matched firms, i and j. Their relative odds (odds ratio) of importing are $\frac{p_i(1-p_j)}{p_j(1-p_i)} = \frac{\exp(\beta X_i+\gamma Z_i)}{\exp(\beta X_j+\gamma Z_j)} = \exp[\gamma(Z_i - Z_j)]$, where the second equality follows from the fact that both firms have the same covariates (as implied by matching). Rosenbaum (2002) shows that this relationship implies the following bounds on the odds ratio: $\frac{1}{e^\gamma} \leq \frac{p_i(1-p_j)}{p_j(1-p_i)} \leq e^\gamma$. If the odds ratio $e^\gamma = 1$, the two matched firms have the same probability of importing. If instead $e^\gamma > 1$, this probability differs, even though the two firms have the same observed characteristics. For example, if the odds ratio $e^\gamma = 2$, the two matched firms differ in their odds of importing by a factor of 2, or 100%. In this sense, e^γ measures the extent of deviation from the baseline setting under the CIA.

The sensitivity analysis evaluates how inference about the ATT is altered by changing the odds ratio e^γ. To this purpose, following Di Prete and Gangl (2004), I progressively increase e^γ and, at each level, calculate the Wilcoxon signed rank test for the null hypothesis that importing has no effect (i.e., that the baseline ATT is zero).[36] As shown by Rosenbaum (2002), for fixed $e^\gamma \geq 1$, this test statistic is bounded by two known distributions. If $e^\gamma = 1$, the upper and lower bounds coincide and are equal to the baseline scenario under the CIA. For increasing e^γ, the bounds move apart and the confidence interval on the ATT becomes wider, reflecting the uncertainty in the test statistic in the presence of unobserved selection bias. The level of e^γ at which the 90% confidence

[36] This test is used for continuous outcomes. In the case of binary outcomes, it is replaced by the Mantel and Haenszel test; see, e.g., Becker and Muendler (2008). It should be noted that the test requires random samples, so treated and control firms must first be made similar in terms of the covariates: PSM does the job.

interval starts including zero is the 'critical' odds ratio. The higher it is, the more an unobserved confounder (not included in the vector X) would have to alter the odds of importing to completely determine the ATT.[37]

3.2.2 Calibrated and Killer Confounders (Ichino et al., 2008)

This approach consists of characterizing the distribution of Z by imposing a small set of parameters, which govern the correlation of Z with treatment and outcome. Using these parameters, a value of Z is simulated for each firm. The propensity score and the ATT are then reestimated by adding the simulated Z to the matching variables. By comparing the ATT estimated with and without Z, one can assess how sensitive the baseline estimate is to a specific deviation from the CIA: namely, to the deviation that would arise due the impossibility of observing a confounder whose distribution is similar to the one implied by the chosen configuration of parameters.

Ichino et al. (2008) characterize the distribution of Z through four parameters: $\pi_{kh} \equiv \Pr(Z = 1|IMP = k, \overline{ESH} = h) = \Pr(Z = 1|IMP = k, \overline{ESH} = h, X)$, with $k, h \in \{0, 1\}$; these parameters measure the probability that $Z = 1$ in each of the four groups defined by treatment status and discretized outcome (denoted by $\overline{ESH}$).[38] Given a set of π_{kh}, a value of Z is attributed to each firm, depending on which of the four groups it belongs. Z is then added to the matching variables used to estimate the propensity score and to calculate the ATT. For fixed π_{kh}, the matching estimation is repeated R times ($R = 100$ in my case), and the ATT is retrieved by averaging out the individual estimates over the distribution of the simulated Z.[39]

Following Ichino et al. (2008), I use two complementary approaches to select the parameters π_{kh}. As for the first approach, I choose these parameters to make the distribution of Z mimic the empirical distribution of the covariates ('calibrated' confounders).[40] This approach allows me to study whether the baseline ATT is robust to deviations from the CIA that would arise from the

[37] I perform this sensitivity analysis using the Stata routine `rbounds` (Di Prete and Gangl, 2004).

[38] This sensitivity analysis can be applied either to a binary outcome or to a binary transformation of a continuous outcome (in this second case, the estimated ATT refers to the continuous outcome). Following Nannicini (2007), I thus discretize ESH by setting at one (zero) the observations above (below) the sample median. Z is assumed to be i.i.d. in the four cells defined by the Cartesian product between IMP and $\overline{ESH}$.

[39] The standard error is computed as $se = \sqrt{se_W^2 + \left(1 + \frac{1}{R}\right) se_B^2}$, where se_W^2 is the average variance of the ATT across simulations, whereas se_B^2 is the average deviation of the ATT from its mean.

[40] For instance, suppose I want Z to mimic the distribution of the indicator for ICT use. Then, I will set $\pi_{11} = 0.81$ because, in my sample, 81% of the importers with $\overline{ESH} = 1$ also use ICT. By the same reasoning, I will set $\pi_{10} = 0.73$, $\pi_{01} = 0.55$, and $\pi_{00} = 0.40$. Note that in the simulations I still control for all covariates. Hence, this first approach is different from simply excluding a variable from the vector X.

impossibility of observing confounders distributed similar to the observed characteristics. However, the set of confounders that can be characterized with this approach is quite limited and specific. Moreover, the results may be sensitive to the behavior of the covariates.

For the above reasons, I complement the first approach with a second one, in which I explore a full grid of π_{kh} in search for the confounders that would drive the ATT to zero ('killer' confounders). I restrict attention to confounders with a positive influence on both the untreated outcome and the treatment, because they could give rise to a positive and significant ATT even if importing had no effect on relative labor demand. As shown by Ichino et al. (2008), these confounders require the following restrictions on the parameters: $d \equiv \pi_{01} - \pi_{00} > 0$ and $s \equiv \pi_{1\cdot} - \pi_{0\cdot} > 0$, where $\pi_{1\cdot}$ and $\pi_{0\cdot}$ measure the probability that $Z = 1$ by treatment status only (note that $d = s = 0$ under the baseline ATT). I thus examine all confounders obtained by increasing d and s by 0.1 up to 0.4. Note that d and s determine the sign of the effects of Z on $\overline{ESH}_0$ and IMP, whereas the magnitude of these effects depends also on the correlation between Z and X.[41] To quantify these magnitudes, I follow Ichino et al. (2008) and, at each simulation of Z, estimate logit models for $\Pr(\overline{ESH} = 1|IMP = 0, Z, X)$ and $\Pr(IMP = 1|Z, X)$. Then, I take the average odds ratio of Z from the former model as a measure of the 'outcome effect' (Γ) of the confounder, and the average odds ratio of Z from the latter model as a measure of the 'selection effect' (Λ). The higher are the values of Γ and Λ needed to drive the ATT to zero, the more robust is the baseline ATT to violations of the CIA.[42]

4 Results

Using the methodology discussed above, I now show that importing inputs induces skill upgrading. To start off, I estimate the propensity score, asses matching quality, and comment on the baseline estimates of the ATT (Section 4.1). Then, I present a number of robustness checks and extensions

[41] Even though the conditional distribution of Z given IMP and $\overline{ESH}$ is independent of X (see the expression for π_{kh} above), Z and X are correlated in the data due the association of X with IMP and $\overline{ESH}$. See Ichino et al. (2008) for details.

[42] This sensitivity analysis is implemented with the Stata routine `sensatt` (Nannicini, 2007). The analysis with killer confounders also uses a Matlab code developed by Nannicini, which yields all the π_{kh} parameters for which $0.1 \leq d, s \leq 0.4$. The code requires the user to impute the following information. (1) $\Pr(Z = 1)$ and $\pi_{11} - \pi_{10}$. Since these quantities do not represent a threat to the baseline ATT, I keep them fixed at 0.45 and zero, respectively (similar to Ichino et al., 2008). (2) $\Pr(IMP = k)$ and $\Pr(\overline{ESH} = h|IMP = k)$. I set these quantities at their sample analogues. In particular, the share of importers is 0.287, whereas the shares of firms with $\overline{ESH} = 1$ equal 0.589 among importers and 0.456 among non-importers.

(Section 4.2). Finally, I discuss the sensitivity of the baseline estimates to selection on unobservables (Section 4.3).

4.1 Baseline Results

I estimate the ATT for four specifications of the propensity score. In the first specification, the vector X contains the proxies for structural characteristics, trade status, and use of ICT, plus full sets of country-industry and year dummies. In the second specification, X adds the controls for ownership status. In the third specification, X further includes the proxies for competition, market, and business environment. Finally, in the fourth specification, X adds the controls for relative labor supply, and country-industry-year dummies replace the country-industry and year effects used in the previous models. All variables enter linearly in all specifications, as higher-order terms do not improve the balancing tests.

Table 5 estimates the four specifications of the propensity score by logit. The coefficients generally have the expected sign and are consistent with the descriptive statistics reported in Table 3. In particular, the probability of importing increases with firm size, and is higher for firms that also export, use ICT, are foreign participated, compete on national or foreign markets, and serve multinational enterprises. It is instead lower for state-owned and privatized firms. Moreover, after controlling for other observed characteristics, the importing probability is only weakly correlated with proxies for relative labor supply; if anything, the estimated coefficients suggest filling skilled jobs to be relatively more difficult for importers.

Table 6a assesses matching quality. Only a minor share of importers gets lost by imposing the common support restriction (between 0.1 and 0.9% across the four specifications). Moreover, matching greatly reduces the median standardized bias (by 81-89%), and the value of the remaining bias in the matched samples is very small (around 2%).[43] Similarly, the pseudo-R^2 drops to zero after matching, suggesting the covariates to have no explanatory power for predicting import status in the matched samples. Overall, this evidence reassures that PSM is successful at balancing the distribution of covariates between importers and matched non-importers.[44]

[43] This is in line with figures reported in previous studies, e.g., Lechner (2002) and Sianesi (2004).

[44] Note, also, that the ratio of treated-to-control observations is fairly large, roughly one-third. In this case, matching quality may be improved by using replacement, because the same control unit can be used more than once. Unreported calculations show, indeed, that the balancing tests are slightly worse without using replacement; moreover, the estimates of the ATT are slightly less conservative (see Section 4.2). For these reasons, I use nearest-neighbor

Finally, Table 6b reports the baseline ATT, with analytical and bootstrapped standard errors shown in square and round brackets, respectively. All ATT are positive and statistically significant beyond the 1% level, independent of the standard error. The point estimates are quite stable across the four specifications: in particular, they imply that importing inputs raises the employment share of skilled labor by about 4.5 p.p.; this is roughly 40% of the unconditional difference between importers and non-importers (see Table 3d). Interestingly, the ATT are systematically lower (by almost 1 p.p.) than the OLS estimates reported in Table 4, suggesting linear regressions to yield upward biased coefficients even controlling for the same covariates.

4.2 Robustness and Extensions

I now extend the baseline analysis to allow for: (1) alternative matching estimators; (2) alternative estimation samples; (3) alternative definitions of outcome and treatment; and (4) cross-country heterogeneity in the ATT. To save space, in this and the next section I focus on the fourth (and richest) specification of the propensity score.[45]

4.2.1 Alternative Matching Estimators

Bias and variance of the ATT may vary across matching estimators, because each estimator assigns a different number of controls to the treated units and a different weight to the controls.[46] Hence, Table 7a presents the results obtained with alternative matching estimators. To begin with, I implement nearest-neighbor matching without replacement, while ranking importers either in ascending or in descending order of their propensity score (columns (1) and (2)). This estimator may not yield matches of the highest quality when the propensity score distribution is very different between treated and controls, or when the available number of controls is not very large. In my case, it yields larger estimates than matching with replacement. In column (3), I thus revert to nearest-neighbor matching with replacement, but allow for multiple (ten) matches. The ATT is very close to the baseline estimate.

In columns (4) and (5), I perform caliper and radius matching. For each treated unit, these estimators select the matched controls within a maximum distance ('caliper') from its propensity

matching with replacement as my baseline estimator.

[45] All results hold also for the other specifications, and are available upon request.

[46] See Frölich (2004) for an extensive discussion of the finite-sample properties of various PSM estimators.

score: caliper matching picks only the closest control within the caliper, whereas radius matching uses all controls available therein. Note that, in both cases, the ATT is identical to the baseline one. In column (6), I use stratification matching, which computes the ATT as the average outcome difference between treated and control units, within the same intervals ('strata') of the propensity score.[47] Also in this case, the point estimate is very close to that in Table 6b.

Next, I use kernel and local linear regression matching (columns (7) and (8)). These estimators pair the treated units to a weighted average of all the control units, with weights depending on the distance between the propensity scores of the two groups. Note that the ATT are very close to the baseline estimate. Finally, I combine both stratification and matching with regression (columns (9) and (10)).[48] These estimators accommodate potential remaining differences in the distribution of covariates between treated and controls. Note that, if anything, their estimates are larger than the baseline ATT.

4.2.2 Alternative Estimation Samples

The country-industry dummies included among the matching variables account for unobserved, time-invariant, country-industry heterogeneity; at the same time, the year dummies purge common macroeconomic shocks. To further control for country, industry, and time characteristics, I now reestimate the propensity score, and reimplement matching, separately by year, by year and country, and by year, country, and sector (manufacturing and services). In this way, I no longer force the covariates to affect the importing probability equally over the entire sample. Moreover, I further ensure that importers get matched to similar non-importers, because matching is progressively restricted to more homogeneous groups of firms. The results are in Table 7b, columns (1)-(3). Reassuringly, all ATT are positive, very precisely estimated, and close to the baseline estimates.[49]

Next, I estimate the ATT separately on each wave of the WBES, rather than pooling the data as done so far (columns (4) and (5)). Both estimates are positive, statistically significant, and similar

[47] The number of strata is chosen so that the covariates are balanced within each stratum. This estimator is implemented using the Stata routine `atts` (Becker and Ichino, 2002).

[48] In particular, as for column (9), I first divide the propensity score into strata, and regress the outcome on treatment and covariates separately for each stratum. Then, I compute the ATT as the weighted average of the individual estimates across all strata. As for column (10), I first construct a matched sample using nearest-neighbor matching with replacement. Then, I obtain the ATT by regressing the outcome on treatment and covariates using the matched sample.

[49] Note that results in column (3) refer to the second specification of the propensity score, because, due to small subsamples, the ATT cannot be computed for richer models.

to that in Table 6b. Finally, I estimate the ATT separately on firms interviewed only once and on firms interviewed twice (columns (6) and (7)). The ATT are positive and precisely estimated in both subsamples.

4.2.3 Alternative Definitions of Outcome and Treatment

In the previous sections, I have constructed the outcome variable using information on the educational composition of firms' workforce. To provide additional insight into how imported inputs affect the relative demand for skilled labor, I now exploit information on occupations. In particular, I redefine the outcome variable as the employment share of non-production or white-collar workers. I use these new variables in Table 7c, columns (1) and (2). Note that the ATT are positive and precisely estimated in both cases.

Next, I consider alternative definitions of importers. To begin with, I widen the notion to include also firms purchasing foreign inputs indirectly, i.e., through domestic distributors. This definition is more comprehensive than the benchmark one, but it is also rougher and less consistent with studies based on custom declarations data, which, generally, only encompass direct importers (see, in particular, Bernard et al., 2007, and Bernard et al., 2009). The results, reported in column (3), are consistent with my baseline evidence, although the estimate is slightly less precise. Finally, I define importers as firms purchasing at least 25 or 50% of their inputs directly from abroad (columns (4) and (5)). The ATT are positive and highly significant in both cases. Interestingly, the point estimate increases with the threshold, suggesting the effect of importing to be stronger the more the firm relies on foreign inputs.

4.2.4 Cross-Country Heterogeneity

So far, I have constrained the ATT to be equal across countries, so as to take advantage of larger sample sizes and obtain more precise and stable estimates. I now apply PSM separately on each country, in order to gather country-specific estimates of the ATT. Then, I use these estimates for two purposes: first, to verify that the aggregate results are not just driven by a handful of countries and, second, to discuss how the magnitude of the effect of importing depends on country characteristics.

The individual ATT are reported in Table A2. Not surprisingly, due to small sample sizes, country-specific estimation inflates the standard errors and yields less precise estimates. However, the pattern of sign is noteworthy. In particular, the ATT are positive for the vast majority of countries (23 to 25 depending on the specification), and the few negative estimates are never robust across models. Overall, this suggests the average ATT to provide a fairly faithful description of the sign of the effect of imported inputs.

Next, I discuss how the magnitude of the effect depends on country characteristics. To provide context for the analysis of the mechanisms in Section 5, I focus on the following variables: per capita income and abundance of production factors. I compute the average ATT (weighted by analytical standard errors) for two groups of countries, with below-average and above-average values of each characteristic.[50] I find the ATT to be always larger for the former group: 0.086 vs. 0.022 when using per capita income, 0.057 vs. 0.048 when using skill abundance, and 0.071 vs. 0.037 when using capital abundance. Overall, this suggests the effect of importing to be stronger in poorer and less endowed economies.

4.3 Assessing the Sensitivity of the Estimates to Selection on Unobservables

I now study how sensitive the baseline estimates are to violations of the CIA due to unobservable factors. To this purpose, I use the sensitivity analyses discussed in Section 3.2. In addition, I exploit the longitudinal dimension of the data and estimate panel regressions controlling for firm fixed effects.

4.3.1 Rosenbaum Bounds

I calculate the significance level of the baseline ATT at increasing values of the odds ratio e^{γ}. I find the critical odds ratio to be 1.20. Hence, firms with the same observed characteristics can differ in their odds of importing by as much as 20%, before the confidence interval on the ATT starts including zero. It should be noted that this is a worst-case scenario: a critical value of 1.20 does not mean that unobserved selection bias is present, nor that importing has no effect, but simply that an unobserved characteristic outside the vector X would need to have an odds ratio of 1.20 to overturn the ATT.

[50] I focus on the fourth specification of the propensity score. I use data on per capita income and capital abundance for 2003, and on skill abundance for 2005.

To have a sense of how strong this confounder would have to be, I compare the critical odds ratio with the net effects of my covariates, as implied by the coefficients of the propensity score models reported in Table 5. A critical level of 1.20 corresponds to the net effect of increasing the employment growth rate in the mean firm from zero[51] to about 40% ($\exp(0.448 \cdot 0.4) \approx 1.20$), or the price-cost margin from 21 to about 65%. One would have to question the robustness of the baseline estimates, if she believed it plausible that an unobserved firm characteristic (outside the rich set of covariates used in the matching exercise) could have such a large impact on the odds of importing.

4.3.2 Calibrated and Killer Confounders

In Table 8, I perform the sensitivity analysis with calibrated confounders. In the first row, I replicate the baseline ATT from Table 6b. In each of the following rows, I simulate a confounder distributed similar to the covariate indicated in the first column; then, I reestimate the ATT by adding this confounder to the matching variables. Note that all ATT are positive, statistically significant, and close to the baseline estimate, implying that none of the calibrated confounders is able to wash out the main result. The most harmful deviation from the CIA occurs under a confounder calibrated to mimic the indicator for ICT use, in which case the ATT is smaller than the baseline one by 1.3 p.p..[52] Nevertheless, the point estimate still remains sizeable: specifically, it implies that importing inputs raises the employment share of skilled labor by 3 p.p., i.e., roughly 25% of the unconditional difference between importers and non-importers.

Next, I characterize the confounders that would drive the ATT to zero (killer confounders). To this purpose, in Table 9, I simulate 16 different confounders, by increasing the value of d (along each column) and the value of s (along each row) from 0.1 to 0.4. In the heading of each row, I report the value of d and the associated range of variation in the outcome effects (Γ) of the confounders. Similarly, in the heading of each column, I report the value of s and the associated range of variation in the selection effects (Λ). Finally, in each cell, I show the ATT [standard error] estimated by adding the respective confounder to the matching variables. The results suggest that both Γ and Λ have to be very high for the confounders to kill the baseline ATT. For instance, most

[51] See Table A3.

[52] This finding is broadly consistent with some trends occurred in transition countries over the recent past. In particular, increased trade openness and faster technical change - both important characteristics of the transition process - have explained a non-negligible part of the rising demand for skilled labor in these countries (see, e.g., Aghion and Commander, 1999, and Commander and Kollo, 2008).

calibrated confounders would fall in the top-left cell of Table 9, as they exhibit small values of Γ and Λ (see the last two rows of Table 8). Hence, even unobservables with much stronger outcome and selection effects would not overturn the baseline result.

4.3.3 Panel Regressions

Finally, I estimate panel regressions controlling for firm fixed effects. This approach further accounts for unobserved, time-invariant, firm characteristics, but unlike PSM requires parametric assumptions. The effect of importing is identified through firms that switch import status between 2002 and 2005.[53]

The results are in Table 10. In column (1), I estimate a baseline specification without controls. In column (2), I control for country-industry-year effects, which account for shocks specific to country-industry pairs. Finally, in columns (3)-(6), I progressively add the four sets of covariates. Reassuringly, the coefficient on the importer indicator is positive and precisely estimated across the board.

5 Discussion of Possible Mechanisms

In the previous section, I have shown that imported inputs induce skill upgrading. Inspired by the recent empirical literature, I now discuss two possible mechanisms behind this result. Specifically, I consider that imported inputs may work by: (1) leading firms to engage in skill-intensive activities; (2) substituting for unskill-intensive stages of production. My data is not suitable to run a rigorous test of these mechanisms. Nevertheless, the suggestive evidence reported in this section will still contribute useful insight into which channel may be more relevant for these countries. In addition, it will be helpful to link the paper more strictly to other strands of research on imported inputs.

5.1 Skill-Intensive Activities

Recent studies show that importing is often associated with other activities undertaken by firms. In turn, some of these activities may be associated with a higher relative demand for skilled labor. Accordingly, foreign inputs may induce skill upgrading by leading firms to engage in skill-intensive

[53] 222 firms out the 1426 interviewed in both waves of the WBES.

activities. The literature has not extensively studied this mechanism. In this section, I provide suggestive evidence on it. To this purpose, I study the correlations between imported inputs and a number of firms' activities, and between the latter and relative skilled employment. In particular, given the available information in the WBES, I focus on the following activities: production of new goods, product quality upgrading, R&D and technology adoption.

To provide context, I first summarize the existing empirical studies on the effects of imported inputs on these activities. Working on India, Goldberg et al. (2010a,b) show that imports expand the range of available inputs and thus allow firms to produce more products.[54] Working on Colombia, Kugler and Verhoogen (2009, 2011) show that foreign inputs are qualitatively superior to domestic inputs, and that higher input quality is associated with higher output quality (which, in turn, is associated with higher relative demand for skilled labor; see Verhoogen, 2008). Finally, other studies show that importing is a channel of technology diffusion, especially from developed to industrializing countries.[55] These studies also suggest that importers often have to perform complementary activities, such as R&D, to develop the absorptive capacity needed to adopt the technologies embodied in the foreign inputs (Keller, 2004).

Turning to the analysis, I use a total of six binary indicators to proxy for these three activities. As for production of new goods, I construct a dummy for whether the firm develops a new product, and another one for whether it exports to a new country. As for product quality upgrading, I construct a dummy for whether the firm obtains a new quality accreditation, and another one for whether it has positive marketing expenditure.[56] Finally, as for R&D and technology adoption, I construct a dummy for whether the firm acquires a new technology, and another one for whether it performs R&D.[57]

To begin with, I report suggestive evidence that importing may lead firms to engage in these activities. The results are in Table 11a. In the first row, I regress the six dummies on the importer indicator, controlling for time and country-industry effects. Note that importers are more likely than non-importers to perform each activity. In the following rows, I estimate the ATT for the four

[54] See also Colantone and Crinò (2011) for recent related evidence on 25 EU countries.

[55] See, among others, Coe et al. (1995, 2009), Keller (2002), Caselli and Wilson (2004), and Acharya and Keller (2009). See also Barba Navaretti and Tarr (2000) for a review.

[56] According to Sutton (1991), and Kugler and Verhoogen (2011) more recently, the scope for quality upgrading is related to marketing expenditure.

[57] See Table A3 for a more detailed description of these variables.

specifications of the propensity score, in order to account for differences in observed characteristics between importers and non-importers.[58] All estimates remain positive and very precise. In the remaining rows, I perform the main robustness checks illustrated in Section 4.2, and report as well the critical odds ratios obtained with the Rosenbaum bounds approach. All these exercises lend support to the evidence emerging from the baseline ATT.

Next, I study the relationship between the three activities and skill upgrading. To this purpose, I regress the share of skilled employment on the six dummy variables, controlling for time and country-industry effects. The results are in Table 11b. The first row refers to univariate regressions, whereas the second row contains a multivariate specification. Note that all correlations are positive, although in the multivariate specification the coefficients on the R&D/technology dummies are not significant. Overall, this suggests skill upgrading to be associated with these three activities, but especially so with the production of new and better products.

5.2 Substitution of Unskill-Intensive Production Stages

In their seminal work on offshoring and wage inequality, Feenstra and Hanson (1999) show that imported inputs have substantially increased the relative demand for skilled labor in the U.S.. The vast literature spurred by their work reports similar evidence for many other industrialized countries.[59] The following mechanism underlies these results. The relative wage of unskilled workers is higher in developed than in developing countries, because the relative abundance of unskilled labor is lower in the former than in the latter economies. Hence, firms operating in rich countries transfer unskill-intensive production stages to poorer countries, and substitute these stages with imported inputs. As a result, their relative demand for skilled labor increases.

Based on the evidence presented before, I speculate that, for the transition countries in my sample, this mechanism may be less relevant than the one discussed in Section 5.1. First, note that the 27 countries mostly source their inputs from richer and more skill-abundant economies (Table 2). The observed differences in factor endowments are thus largely inconsistent with the offshoring of unskill-intensive production stages. Second, note that the effect of importing is stronger in the

[58] The only difference between these specifications and those in Table 6b is in the outcome variables.

[59] A non-exhaustive list of contributions includes Hijzen et al. (2005), Biscourp and Kramarz (2007), and Becker et al. (2009). Updated surveys of this literature can be found in Feenstra and Hanson (2003), Hijzen (2005), Crinò (2009), and Feenstra (2010).

subsample of poorer and less endowed countries (Section 4.2.4). In these countries, firms may be more likely to use imports for accessing more and better inputs, than for replacing basic production stages.

6 Conclusion

I have studied the effect of imported inputs on relative skilled labor demand, using firm-level data for 27 transition countries and PSM techniques. I have found robust evidence that importing inputs induces skill upgrading: it explains roughly one-quarter of the unconditional difference in the share of skilled employment between importers and non-importers. Next, I have explored possible mechanisms behind this result. In particular, building on the received literature, I have reported suggestive evidence that imported inputs may lead firms to engage in skill-intensive activities, such as production of new goods, improvements in product quality and, to a lesser extent, R&D and technology adoption.

In recent years, a number of firm-level studies have dramatically improved our understanding of how imported inputs affect the performance and operations of firms in industrializing countries. This paper contains novel evidence on the implications of foreign inputs for the skill composition of firms' employment, an issue on which the literature has not yet reached definite conclusions. Overall, my results may bring about some interesting policy implications. In particular, consistent with OECD (2005), they suggest that policies aimed at easing firms' access to foreign markets should be accompanied by interventions aimed at improving the level of formal education and the working skills of the employees.

The transition countries analyzed in this paper represent an interesting case study, due to some of their peculiarities. However, my findings may be more general and may apply also to different contexts. In particular, they may hold true in developing countries that are highly dependent on foreign inputs, and that mostly source them from rich and well endowed economies. It is in these cases, in fact, that the mechanism highlighted in this paper may be more relevant. Exploring whether my results extend to such contexts is thus a promising avenue for future research. Unveiling additional mechanisms is a second interesting line of analysis, which may offer further insight for the design of effective policies.

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Table 1 - Firms, Importers, and Import Shares

	All Firms	Importers		Import Shares	
	Number	Number	Share	Mean	Std. Dev.
Whole Sample	14008	4016	0.287	0.540	0.345
Albania	371	208	0.561	0.670	0.337
Armenia	358	94	0.263	0.653	0.349
Azerbaijan	367	128	0.349	0.606	0.319
Belarus	563	176	0.313	0.552	0.345
Bosnia and Herzegovina	349	150	0.430	0.580	0.345
Bulgaria	542	149	0.275	0.533	0.350
Croatia	339	145	0.428	0.548	0.341
Czech Republic	591	162	0.274	0.441	0.321
Estonia	362	137	0.378	0.521	0.335
FYR Macedonia	357	147	0.412	0.604	0.357
Georgia	339	108	0.319	0.680	0.322
Hungary	553	168	0.304	0.466	0.354
Kazakhstan	535	143	0.267	0.555	0.321
Kyrgyz Republic	342	112	0.327	0.657	0.327
Latvia	371	113	0.305	0.586	0.354
Lithuania	381	134	0.352	0.505	0.353
Moldova	360	120	0.333	0.592	0.332
Poland	1050	203	0.193	0.434	0.338
Romania	546	105	0.192	0.528	0.358
Russia	1062	186	0.175	0.535	0.349
Serbia and Montenegro	517	193	0.373	0.589	0.346
Slovak Republic	363	174	0.479	0.476	0.341
Slovenia	395	195	0.494	0.460	0.301
Tajikistan	374	83	0.222	0.629	0.326
Turkey	1063	203	0.191	0.371	0.285
Ukraine	1036	195	0.188	0.519	0.365
Uzbekistan	522	85	0.163	0.551	0.325

Figures in the last two columns refer to the share of inputs imported directly, and are computed for the subsample of importing firms. Source: World Bank Enterprise Surveys, 2002 and 2005.

Table 2 - Main Providers of Foreign Inputs and Country Characteristics

Country Name		Per Capita Income		Skill Abundance		Capital Abundance	
Sample Country	Main Provider	Sample Country	Main Provider	Sample Country	Main Provider	Sample Country	Main Provider
Albania	Italy (0.50)	3520	28882	3.3	5.2	12058	78878
Armenia	Belgium (0.44)	2567	31492	9.6	16.6	2341	91056
Azerbaijan	Turkey (0.20)	2880	8397	-	5.0	2995	14594
Belarus	Germany (0.39)	6252	30948	-	10.7	8791	84038
Bosnia and Herzegovina	Germany (0.22)	5884	30948	-	10.7	8916	84038
Bulgaria	Germany (0.25)	6419	30948	9.8	10.7	16997	84038
Croatia	Germany (0.25)	9683	30948	3.5	10.7	18402	84038
Czech Republic	Germany (0.39)	16932	30948	5.1	10.7	36684	84038
Estonia	Finland (0.42)	10436	28261	14.3	5.5	30192	74264
FYR Macedonia	Italy (0.20)	6336	28882	-	5.2	11933	78878
Georgia	Germany (0.32)	2956	30948	-	10.7	2336	84038
Hungary	Germany (0.30)	13272	30948	9.4	10.7	31220	84038
Kazakhstan	Russia (0.45)	5112	8716	8.0	7.7	9946	26401
Kyrgyz Republic	China (0.39)	1649	2885	6.4	2.6	1395	8316
Latvia	Russia (0.40)	8282	8716	7.4	7.7	9378	26401
Lithuania	Germany (0.23)	8934	30948	8.2	10.7	8123	84038
Moldova	Germany (0.28)	1580	30948	5.7	10.7	6929	84038
Poland	Germany (0.28)	11486	30948	6.3	10.7	23734	84038
Romania	Italy (0.25)	6114	28882	4.5	5.2	25372	78878
Russia	Germany (0.22)	8716	30948	7.7	10.7	26401	84038
Serbia and Montenegro	Germany (0.15)	4910	30948	6.5	10.7	13149	84038
Slovak Republic	Germany (0.36)	13040	30948	4.7	10.7	33609	84038
Slovenia	Germany (0.22)	19101	30948	5.9	10.7	40490	84038
Tajikistan	Russia (0.35)	1061	8716	3.0	7.7	1596	26401
Turkey	Germany (0.18)	8397	30948	5.0	10.7	14594	84038
Ukraine	Russia (0.28)	3918	8716	19.5	7.7	14135	26401
Uzbekistan	Korea (0.25)	1462	18856	-	13.7	2924	63765

For any given sample country, the main provider is the economy accounting for the largest share of total imported inputs (reported in round brackets). *Per capita income* is expressed in 2005 international dollars per person. *Skill abundance* is the share of population with complete tertiary schooling. *Capital abundance* is the capital stock per worker, expressed in 2005 international dollars per person. All figures refer to the year 2000.

Table 3 - Outcome and Covariates in Importing and Non-Importing Firms

	a) Importers		b) Non-Importers		c) Simple Difference		d) Conditional Diff.	
	Mean	Std. Dev.	Mean	Std. Dev.	Coeff.	Std. Err.	Coeff.	Std. Err.
1) Outcome								
Share of workers with tertiary+ education	0.323	0.301	0.249	0.290	0.074***	[0.006]	0.107***	[0.005]
2) Covariates								
2.1) Structural Characteristics, Trade Status, and Use of ICT								
Ind: 50-249 empl (3 yrs bef)	0.241	0.428	0.176	0.381	0.065***	[0.008]	0.070***	[0.008]
Ind: 250+ empl (3 yrs bef)	0.191	0.393	0.076	0.264	0.115***	[0.007]	0.101***	[0.007]
Δlabor productivity (prev 3 yrs)	0.222	0.548	0.126	0.509	0.096***	[0.010]	0.099***	[0.011]
Δcapital intensity (prev 3 yrs)	0.167	0.436	0.112	0.380	0.055***	[0.008]	0.045***	[0.009]
Δemployment (prev 3 yrs)	0.006	0.120	0.004	0.103	0.002	[0.002]	0.003	[0.003]
Capacity utilization (3 yrs bef)	0.776	0.212	0.798	0.210	-0.023***	[0.004]	-0.020***	[0.004]
Age	16.727	20.495	14.853	17.232	1.874***	[0.367]	1.154***	[0.360]
Ind: Uses ICT	0.776	0.417	0.472	0.499	0.304***	[0.008]	0.301***	[0.008]
Ind: Exporter	0.488	0.500	0.133	0.340	0.355***	[0.009]	0.312***	[0.009]
2.2) Ownership Status								
Ind: State owned	0.085	0.279	0.117	0.321	-0.031***	[0.005]	-0.021***	[0.006]
Ind: Foreign owned	0.170	0.376	0.034	0.182	0.136***	[0.006]	0.137***	[0.006]
Ind: Privatized	0.158	0.365	0.134	0.341	0.024***	[0.007]	0.009	[0.007]
2.3) Competition, Market, and Business Environment								
Ind: Faces significant import competition	0.656	0.475	0.457	0.498	0.198***	[0.009]	0.142***	[0.010]
Ind: Competes on national mkt	0.865	0.341	0.663	0.473	0.202***	[0.007]	0.146***	[0.007]
Ind: Is credit constrained	0.407	0.491	0.444	0.497	-0.037***	[0.009]	-0.030***	[0.010]
Ind: Has gvt among customers	0.133	0.340	0.127	0.333	0.006	[0.006]	0.017**	[0.007]
Ind: Has MNEs among customers	0.117	0.322	0.055	0.228	0.062***	[0.006]	0.066***	[0.006]
Ind: Received subsidies from ntl gvt (prev 3 yrs)	0.055	0.229	0.034	0.182	0.021***	[0.004]	0.012***	[0.004]
Ind: Received subsidies from loc gvt (prev 3 yrs)	0.021	0.143	0.028	0.165	-0.007**	[0.003]	-0.002	[0.003]
Price-cost margin	0.208	0.128	0.211	0.146	-0.003	[0.003]	0.007**	[0.003]
2.4) Relative Labor Supply								
Ind: Has problems finding necessary skills	0.320	0.467	0.286	0.452	0.034***	[0.009]	0.040***	[0.009]
Weeks to fill a vacancy (white-collar)	2.135	3.780	1.166	2.592	0.970***	[0.065]	0.859***	[0.061]
Weeks to fill a vacancy (blue-collar)	1.380	2.659	1.115	2.438	0.265***	[0.049]	0.159***	[0.051]

Results in panel c) are obtained by regressing each variable on the dummy for importing firms. Results in panel d) are obtained in the same way, but the specifications also control for: country-industry and year effects in the case of outcome and variables sub 2.1)-2.3); country-industry-year effects in the case of variables sub 2.4). All figures refer to the whole sample of countries. Standard errors are robust to heteroskedasticity. ***, **, *: indicate significance at the 1, 5, and 10% level, respectively.

Table 4 - Imported Inputs and Skill Upgrading: Preliminary Evidence

	a) Specification 1	b) Specification 2	c) Specification 3	d) Specification 4
Ind: Importer	0.061***	0.054***	0.051***	0.050***
	[0.006]	[0.006]	[0.007]	[0.007]
Covariates:				
Structural Characteristics, Trade Status, and Use of ICT	yes	yes	yes	yes
Ownership Status	no	yes	yes	yes
Competition, Market, and Business Environment	no	no	yes	yes
Relative Labor Supply	no	no	no	yes
Obs.	11944	11872	9468	8968
R^2	0.29	0.30	0.31	0.33

The dependent variable is the employment share of workers with some university or higher education. In panels a)-c), full sets of country-industry and year dummies are included as well; in panel d), a full set of country-industry-year dummies is included instead. All specifications are estimated by OLS. Standard errors are robust to heteroskedasticity. ***, **, *: indicate significance at the 1, 5, and 10% level, respectively.

Table 5 - Estimation of Propensity Scores

	Specification 1		Specification 2		Specification 3		Specification 4	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Structural Characteristics, Trade Status, and Use of ICT								
Ind: 50-249 empl (3 yrs bef)	0.435***	[0.067]	0.445***	[0.070]	0.396***	[0.080]	0.395***	[0.084]
Ind: 250+ empl (3 yrs bef)	0.856***	[0.088]	0.908***	[0.095]	0.818***	[0.110]	0.831***	[0.118]
Δlabor productivity (prev 3 yrs)	0.130**	[0.054]	0.107*	[0.055]	0.080	[0.059]	0.083	[0.062]
Δcapital intensity (prev 3 yrs)	0.027	[0.067]	0.032	[0.068]	0.065	[0.073]	0.064	[0.079]
Δemployment (prev 3 yrs)	0.359**	[0.154]	0.367**	[0.144]	0.357***	[0.137]	0.448***	[0.146]
Capacity utilization (3 yrs bef)	-0.179	[0.122]	-0.255**	[0.124]	-0.130	[0.141]	-0.095	[0.149]
Age	-0.189***	[0.037]	-0.023	[0.041]	-0.065	[0.047]	-0.078	[0.050]
Ind: Uses ICT	1.363***	[0.063]	1.261***	[0.063]	1.208***	[0.073]	1.207***	[0.077]
Ind: Exporter	1.515***	[0.059]	1.456***	[0.061]	1.396***	[0.070]	1.464***	[0.075]
Ownership Status								
Ind: State owned			-0.612***	[0.104]	-0.513***	[0.124]	-0.531***	[0.130]
Ind: Foreign owned			1.295***	[0.098]	1.176***	[0.110]	1.188***	[0.118]
Ind: Privatized			-0.365***	[0.086]	-0.384***	[0.099]	-0.380***	[0.103]
Competition, Market, and Business Environment								
Ind: Faces significant import competition					0.490***	[0.060]	0.500***	[0.064]
Ind: Competes on national mkt					0.803***	[0.083]	0.906***	[0.092]
Ind: Is credit constrained					-0.024	[0.059]	-0.018	[0.063]
Ind: Has gvt among customers					0.037	[0.092]	0.036	[0.096]
Ind: Has MNEs among customers					0.242**	[0.106]	0.243**	[0.113]
Ind: Received subsidies from ntl gvt (prev 3 yrs)					0.173	[0.167]	0.201	[0.173]
Ind: Received subsidies from loc gvt (prev 3 yrs)					0.377*	[0.213]	0.423*	[0.222]
Price-cost margin					0.428*	[0.222]	0.432*	[0.230]
Relative Labor Supply								
Ind: Has problems finding necessary skills							0.015	[0.068]
Weeks to fill a vacancy (white-collar)							0.040***	[0.011]
Weeks to fill a vacancy (blue-collar)							-0.002	[0.014]
Country-industry dummies	yes		yes		yes		no	
Year dummies	yes		yes		yes		no	
Country-industry-year dummies	no		no		no		yes	
Obs.	11944		11872		9468		8968	
Log-likelihood	-5327.66		-5154.39		-4034.31		-3807.37	
Pseudo-R^2	0.26		0.27		0.29		0.30	

The dependent variable is the indicator for importing firms. Estimation is performed by logit. Standard errors are robust to heteroskedasticity. ***, **, *: indicate significance at the 1, 5, and 10% level, respectively.

Table 6 - Covariate Balancing Tests and Baseline ATT

	Specification 1	Specification 2	Specification 3	Specification 4
	a) Covariate Balancing Tests			
Observations				
Treated	3431	3398	2688	2659
Control	8513	8474	6780	6309
Total	11944	11872	9468	8968
Treated Observations Outside Common Support				
Number	3	6	20	24
%	0.1	0.2	0.7	0.9
Median Standardized Bias				
Before Matching	16.4	14.8	12.3	11.1
After Matching	2.1	1.6	2.0	2.1
Change (%)	-87.1	-89.3	-83.5	-80.7
Pseudo-R^2				
Before Matching	0.16	0.18	0.20	0.20
After Matching	0.00	0.00	0.00	0.01
	b) Baseline ATT			
ATT	0.047***	0.045***	0.042***	0.043***
	[0.011]	[0.011]	[0.013]	[0.013]
	(0.012)	(0.010)	(0.013)	(0.013)

All results are obtained using nearest-neighbor matching with replacement. The outcome variable is the employment share of workers with some university or higher education; the treatment indicator is the dummy for importing firms. In panel b), analytical and bootstrapped standard errors (based on 100 replications) are reported in square and round brackets, respectively. ***, **, *: indicate significance at the 1, 5, and 10% level, respectively.

Table 7 - Robustness and Extensions

	a) Alternative Matching Estimators					b) Alternative Estimation Samples						
	NN, no Repl., Ascending	NN, no Repl., Descending	NN, Repl., 10 Matches	Caliper	Radius	Match. by Year	Match. by Year and Country	Match. by Year, Country, and Sector	Match. on the 1st Wave ('02)	Match. on the 2nd Wave ('05)	Match. on Firms Interv. only Once	Match. on Firms Interv. Twice
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ATT	0.051***	0.051***	0.042***	0.043***	0.043***	0.039***	0.044***	0.054***	0.039*	0.039*	0.048***	0.069*
	[0.008]	[0.008]	[0.011]	[0.013]	[0.010]	[0.010]	[0.011]	[0.009]	[0.019]	[0.018]	[0.015]	[0.028]
	(0.007)	(0.006)	(0.010)	(0.013)	(0.010)	(0.012)	(0.019)	(0.009)	(0.020)	(0.019)	(0.017)	(0.035)

	a) Alternative Matching Estimators (continued)					c) Alternative Definitions of Outcome and Treatment				
	Statification	Kernel	Local Linear Regression	Stratification and Regression	Matching and Regression	Empl. Share of NP Workers	Empl. Share of WC Workers	Dir. & Ind. Importers	Dir. Importers (25% or more)	Dir. Importers (50% or more)
	(6)	(7)	(8)	(9)	(10)	(1)	(2)	(3)	(4)	(5)
ATT	0.041***	0.044***	0.043***	0.057***	0.058***	0.015**	0.044***	0.021*	0.059***	0.072***
	[0.010]	[0.010]	[0.010]	[0.015]	[0.007]	[0.008]	[0.013]	[0.011]	[0.013]	[0.014]
	(0.010)	(0.008)	(0.009)	(0.018)	(0.006)	(0.007)	(0.012)	(0.012)	(0.014)	(0.013)

Unless otherwise indicated, results refer to the fourth specification of the propensity score; moreover, the outcome variable is the employment share of workers with some university or higher education, and the treatment indicator is the dummy for importing firms. In panel a), *NN* stands for nearest-neighbor; caliper and radius matching use a 0.01 caliper; kernel and local linear regression use epanechnikov kernel with 0.06 bandwith. The results in column (3) of panel b) refer to the second specification of the propensity score. In panel c), *NP* stands for non-production and *WC* for white-collar. Analytical and bootstrapped standard errors (based on 100 replications) are reported in square and round brackets, respectively. ***, **, *: indicate significance at the 1, 5, and 10% level, respectively.

Table 8 - Calibrated Confounders

	Coeff.	Std. Err.
Baseline ATT	0.043***	[0.013]
Confounder Behaving Like:		
Ind: 50-249 empl (3 yrs bef)	0.043***	[0.016]
Ind: 250+ empl (3 yrs bef)	0.045**	[0.017]
Δlabor productivity (prev 3 yrs)	0.040**	[0.016]
Δcapital intensity (prev 3 yrs)	0.044***	[0.016]
Δemployment (prev 3 yrs)	0.042**	[0.017]
Capacity utilization (3 yrs bef)	0.044***	[0.015]
Age	0.045***	[0.015]
Ind: Uses ICT	0.030*	[0.019]
Ind: Exporter	0.036*	[0.022]
Ind: State owned	0.045***	[0.016]
Ind: Foreign owned	0.041**	[0.018]
Ind: Privatized	0.043***	[0.015]
Ind: Faces significant import competition	0.046***	[0.017]
Ind: Competes on national mkt	0.046***	[0.017]
Ind: Is credit constrained	0.044***	[0.016]
Ind: Has gvt among customers	0.042***	[0.015]
Ind: Has MNEs among customers	0.043***	[0.016]
Ind: Received subsidies from ntl gvt (prev 3 yrs)	0.043***	[0.016]
Ind: Received subsidies from loc gvt (prev 3 yrs)	0.044***	[0.015]
Price-cost margin	0.043***	[0.015]
Ind: Has problems finding necessary skills	0.046***	[0.016]
Weeks to fill a vacancy (white-collar)	0.038**	[0.016]
Weeks to fill a vacancy (blue-collar)	0.043***	[0.016]
Γ [min. - max.]	0.8 - 2.0	
Λ [min. - max.]	0.7 - 6.8	

Results refer to the fourth specification of the propensity score. The first row replicates the baseline *ATT* and its analytical standard error (see Table 6b). Each of the following rows reestimates the *ATT* by adding to the matching variables a simulated confounder, which is distributed similar to the covariate indicated in the first column (all results are based on 100 simulations of the confounders; analytical standard errors are computed as explained in the text). The last two rows report the minimum and maximum values of the outcome effect (Γ) and selection effect (Λ) of the confounders. Outcome and continuous covariates are discretized, by setting at one (zero) the observations above (below) the sample median. ***, **, *: indicate significance at the 1, 5, and 10% level, respectively.

Table 9 - Characterizing Killer Confounders

	s=0.1, Λ [1.4, 1.5]	s=0.2, Λ [2.2, 2.3]	s=0.3, Λ [3.4, 3.6]	s=0.4, Λ [5.7, 5.9]
d=0.1, Γ [1.6, 1.7]	0.040**	0.037**	0.032*	0.031
	[0.016]	[0.017]	[0.018]	[0.021]
d=0.2, Γ [2.3, 3.0]	0.037**	0.031**	0.023	0.015
	[0.016]	[0.016]	[0.018]	[0.019]
d=0.3, Γ [3.8, 5.4]	0.036**	0.025	0.013	0.002
	[0.017]	[0.016]	[0.018]	[0.020]
d=0.4, Γ [6.4, 11.0]	0.032**	0.020	0.005	-0.011
	[0.016]	[0.017]	[0.019]	[0.020]

The table reports the *ATT* obtained by adding simulated confounders (100 simulations) to the fourth specification of the propensity score. The heading of each row reports the range of variation in the outcome effects (Γ) of the confounders, whereas the heading of each column reports the range of variation in the selection effects (Λ). Analytical standard errors are reported in square brackets. ***, **, *: indicate significance at the 1, 5, and 10% level, respectively.

Table 10 - Panel Regressions

	(1)	(2)	(3)	(4)	(5)	(6)
Ind: Importer	0.045**	0.060***	0.068***	0.064***	0.054**	0.051*
	[0.020]	[0.019]	[0.021]	[0.021]	[0.027]	[0.027]
Covariates:						
Structural Characteristics, Trade Status, and Use of ICT	no	no	yes	yes	yes	yes
Ownership Status	no	no	no	yes	yes	yes
Competition, Market, and Business Environment	no	no	no	no	yes	yes
Relative Labor Supply	no	no	no	no	no	yes
Obs.	2694	2694	2429	2412	1921	1897
R^2	0.01	0.32	0.38	0.38	0.44	0.46

The dependent variable is the employment share of workers with some university or higher education. All specifications are estimated on the panel of firms observed in both periods and control for firm fixed effects. Except for column (1), they also include a full set of country-industry-year dummies. Standard errors are corrected for clustering at the firm level. ***, **, *: indicate significance at the 1, 5, and 10% level, respectively.

Table 11 - Skill-Intensive Activities

Activity:	Production of New Goods		Improvements in Product Quality		R&D and Technology Adoption	
Variable:	Ind: Develops a new product	Ind: Exports to a new country	Ind: Obtains quality accred	Ind: Has positive expend in mktg	Ind: Acquires new tech	Ind: Performs R&D
	a) Imported Inputs and Firms' Activities					
OLS	0.163***	0.172***	0.114***	0.161***	0.109***	0.115***
	[0.010]	[0.008]	[0.007]	[0.010]	[0.009]	[0.008]
ATT, Specification 1	0.100***	0.048***	0.064***	0.088***	0.054***	0.085***
	[0.018]	[0.014]	[0.013]	[0.020]	[0.018]	[0.016]
	(0.019)	(0.020)	(0.016)	(0.018)	(0.020)	(0.016)
ATT, Specification 2	0.082***	0.049***	0.065***	0.067***	0.038**	0.044**
	[0.019]	[0.014]	[0.013]	[0.021]	[0.018]	[0.017]
	(0.021)	(0.017)	(0.016)	(0.023)	(0.021)	(0.020)
ATT, Specification 3	0.068***	0.056***	0.060***	0.075***	0.057***	0.064***
	[0.021]	[0.016]	[0.015]	[0.022]	[0.020]	[0.018]
	(0.025)	(0.023)	(0.018)	(0.026)	(0.020)	(0.021)
ATT, Specification 4	0.092***	0.053***	0.075***	0.074***	0.057***	0.049**
	[0.022]	[0.017]	[0.016]	[0.024]	[0.021]	[0.019]
	(0.023)	(0.024)	(0.023)	(0.026)	(0.027)	(0.023)
NN, No Repl., Ascending	0.111***	0.146***	0.097***	0.118***	0.075***	0.090***
	[0.013]	[0.011]	[0.010]	[0.014]	[0.013]	[0.012]
	(0.029)	(0.063)	(0.034)	(0.036)	(0.027)	(0.033)
NN, No Repl., Descending	0.111***	0.146***	0.098***	0.119***	0.074***	0.089***
	[0.013]	[0.011]	[0.010]	[0.014]	[0.013]	[0.012]
	(0.010)	(0.010)	(0.009)	(0.011)	(0.012)	(0.010)
Kernel	0.086***	0.053***	0.054***	0.080***	0.046***	0.058***
	[0.017]	[0.011]	[0.012]	[0.019]	[0.016]	[0.015]
	(0.016)	(0.018)	(0.017)	(0.017)	(0.017)	(0.018)
Dir. & Ind. Importers	0.087***	0.056***	0.040***	0.051**	0.059***	0.039**
	[0.018]	[0.011]	[0.012]	[0.021]	[0.017]	[0.015]
	(0.022)	(0.016)	(0.014)	(0.023)	(0.021)	(0.016)
Critical Odds Ratio e^{γ}	1.35	1.25	1.55	1.25	1.20	1.20
	b) Firms' Activities and Skill Upgrading					
OLS, Univariate Regressions	0.053***	0.078***	0.046***	0.059***	0.024***	0.050***
	[0.005]	[0.007]	[0.006]	[0.005]	[0.005]	[0.007]
OLS, Multivariate Specification	0.042***	0.054***	0.016**	0.044***	0.000	0.011
	[0.006]	[0.008]	[0.007]	[0.006]	[0.006]	[0.007]

In panel a), the outcome variables are indicated in columns' headings and the treatment indicator is the dummy for importing firms. In panel b), the dependent variable is the employment share of workers with some university or higher education, and the explanatory variables are those indicated in columns' headings: they are used separately in the univariate regressions and jointly in the multivariate specification. Marketing and R&D expenditures are set to zero when missing. OLS estimates control for year and country-industry dummies, and their standard errors are robust to heteroskedasticity. As for the ATT, analytical and bootstrapped standard errors (based on 100 replications) are reported in square and round brackets, respectively. ***, **, *: indicate significance at the 1, 5, and 10% level, respectively.

Table A1 - Imported Inputs and Skill Upgrading: Preliminary Evidence for Individual Countries

	a) Baseline		b) Industry and Year Dummies		c) Specification 1		d) Specification 2		e) Specification 3		f) Specification 4	
	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.	Coeff.	Std. Err.
Albania	0.009	[0.024]	0.031	[0.022]	0.017	[0.024]	0.018	[0.026]	-0.002	[0.027]	-0.017	[0.027]
Armenia	0.126***	[0.036]	0.160***	[0.036]	0.070	[0.043]	0.085**	[0.042]	0.106**	[0.054]	0.081	[0.055]
Azerbaijan	0.130***	[0.034]	0.129***	[0.034]	0.057	[0.040]	0.062	[0.041]	0.032	[0.024]	0.024	[0.025]
Belarus	0.125***	[0.027]	0.120***	[0.027]	0.082***	[0.030]	0.080***	[0.030]	0.030	[0.032]	0.030	[0.035]
Bosnia and Herzegovina	0.068***	[0.025]	0.050**	[0.025]	0.005	[0.028]	0.002	[0.028]	0.049	[0.033]	0.068**	[0.034]
Bulgaria	0.128***	[0.030]	0.170***	[0.030]	0.110***	[0.035]	0.090**	[0.036]	0.065**	[0.026]	0.057**	[0.027]
Croatia	0.098***	[0.028]	0.115***	[0.032]	0.070*	[0.037]	0.070*	[0.038]	0.036	[0.030]	0.030	[0.030]
Czech Republic	0.106***	[0.021]	0.110***	[0.021]	0.071***	[0.025]	0.057**	[0.025]	0.078**	[0.032]	0.076**	[0.033]
Estonia	0.020	[0.032]	0.050	[0.035]	0.066	[0.040]	0.067	[0.041]	0.016	[0.034]	0.006	[0.036]
FYR Macedonia	0.097***	[0.026]	0.107***	[0.025]	0.057*	[0.034]	0.055*	[0.033]	0.083**	[0.035]	0.096**	[0.038]
Georgia	0.152***	[0.038]	0.194***	[0.038]	0.132***	[0.045]	0.131***	[0.045]	0.043	[0.026]	0.032	[0.027]
Hungary	0.045*	[0.025]	0.096***	[0.026]	0.043	[0.030]	0.034	[0.030]	0.051	[0.044]	0.031	[0.045]
Kazakhstan	0.066**	[0.028]	0.081***	[0.029]	0.054*	[0.031]	0.042	[0.030]	0.016	[0.025]	0.024	[0.025]
Kyrgyz Republic	0.092***	[0.035]	0.092***	[0.036]	0.038	[0.041]	0.022	[0.042]	0.075*	[0.040]	0.058	[0.040]
Latvia	0.086**	[0.035]	0.092***	[0.035]	0.007	[0.044]	0.000	[0.044]	0.165***	[0.041]	0.176***	[0.042]
Lithuania	0.060*	[0.031]	0.071**	[0.032]	0.060	[0.037]	0.063*	[0.035]	-0.031	[0.052]	-0.054	[0.057]
Moldova	0.165***	[0.035]	0.193***	[0.032]	0.165***	[0.035]	0.165***	[0.035]	0.049	[0.042]	0.060	[0.045]
Poland	0.075***	[0.022]	0.117***	[0.020]	0.065***	[0.024]	0.046*	[0.025]	0.108**	[0.048]	0.104**	[0.052]
Romania	0.038*	[0.023]	0.052**	[0.023]	0.025	[0.023]	0.024	[0.023]	0.153***	[0.053]	0.166***	[0.055]
Russia	0.159***	[0.028]	0.176***	[0.027]	0.090***	[0.031]	0.081***	[0.030]	0.062	[0.052]	0.073	[0.054]
Serbia and Montenegro	0.093***	[0.023]	0.113***	[0.023]	0.080***	[0.026]	0.068***	[0.026]	0.060*	[0.031]	0.072**	[0.031]
Slovak Republic	0.044	[0.028]	0.070**	[0.028]	0.022	[0.034]	0.021	[0.035]	0.014	[0.034]	0.010	[0.035]
Slovenia	0.033	[0.025]	0.090***	[0.026]	0.045	[0.030]	0.053*	[0.030]	0.042	[0.052]	0.038	[0.055]
Tajikistan	0.096***	[0.030]	0.092***	[0.029]	0.087***	[0.033]	0.080**	[0.034]	-0.030	[0.042]	-0.026	[0.048]
Turkey	0.066***	[0.019]	0.068***	[0.019]	0.020	[0.022]	0.026	[0.022]	0.053	[0.034]	0.061*	[0.034]
Ukraine	0.137***	[0.026]	0.144***	[0.025]	0.062**	[0.028]	0.039	[0.028]	0.075**	[0.037]	0.070*	[0.039]
Uzbekistan	-0.016	[0.034]	0.057*	[0.032]	0.044	[0.032]	0.015	[0.034]	0.017	[0.051]	0.025	[0.054]

Results are obtained by regressing the outcome (employment share of workers with some university or higher education) on the dummy for importing firms. Panel a) does not include any control variable. Panel b) includes full sets of industry and year dummies. Panels c)-f) include the same control variables as the corresponding panels of Table 4 (coefficients unreported). All specifications are estimated by OLS. Standard errors are robust to heteroskedasticity. ***, **, *: indicate significance at the 1, 5, and 10% level, respectively.

Table A2 - Imported Inputs and Skill Upgrading: ATT for Individual Countries

	Specification 1			Specification 2			Specification 3			Specification 4		
	ATT	Std. Err.	Std. Err.	ATT	Std. Err.	Std. Err.	ATT	Std. Err.	Std. Err.	ATT	Std. Err.	Std. Err.
Albania	0.022	[0.040]	(0.039)	0.036	[0.042]	(0.041)	0.004	[0.040]	(0.055)	-0.091**	[0.041]	(0.053)
Armenia	0.142*	[0.067]	(0.073)	0.067	[0.070]	(0.072)	0.093	[0.094]	(0.108)	0.188*	[0.108]	(0.136)
Azerbaijan	0.059	[0.069]	(0.075)	0.020	[0.070]	(0.073)	0.029	[0.080]	(0.092)	-0.045	[0.084]	(0.103)
Belarus	0.039	[0.048]	(0.047)	0.049	[0.047]	(0.049)	0.151***	[0.045]	(0.056)	0.099**	[0.049]	(0.057)
Bosnia and Herzegovina	-0.015	[0.050]	(0.055)	0.014	[0.050]	(0.059)	-0.026	[0.063]	(0.073)	0.001	[0.068]	(0.077)
Bulgaria	0.053	[0.057]	(0.050)	0.050	[0.054]	(0.063)	0.063	[0.068]	(0.074)	0.076	[0.074]	(0.078)
Croatia	0.024	[0.058]	(0.073)	-0.020	[0.060]	(0.075)	0.105	[0.084]	(0.119)	0.021	[0.085]	(0.134)
Czech Republic	0.103*	[0.038]	(0.054)	0.076	[0.052]	(0.057)	0.089*	[0.052]	(0.053)	0.043	[0.058]	(0.059)
Estonia	0.082	[0.069]	(0.057)	-0.002	[0.079]	(0.076)	0.123	[0.079]	(0.086)	0.085	[0.103]	(0.108)
FYR Macedonia	0.019	[0.054]	(0.065)	0.074	[0.055]	(0.061)	0.128***	[0.040]	(0.066)	0.057	[0.067]	(0.067)
Georgia	0.004	[0.087]	(0.082)	-0.003	[0.075]	(0.090)	0.176**	[0.078]	(0.123)	0.222**	[0.090]	(0.108)
Hungary	0.029	[0.047]	(0.052)	0.014	[0.044]	(0.051)	-0.013	[0.047]	(0.067)	-0.038	[0.060]	(0.077)
Kazakhstan	-0.001	[0.047]	(0.045)	0.080	[0.047]	(0.051)	0.024	[0.056]	(0.068)	0.023	[0.055]	(0.077)
Kyrgyz Republic	0.039	[0.071]	(0.070)	0.068	[0.068]	(0.077)	0.067	[0.074]	(0.101)	0.159**	[0.073]	(0.119)
Latvia	-0.032	[0.070]	(0.090)	0.090	[0.069]	(0.076)	0.095	[0.074]	(0.115)	-0.076	[0.090]	(0.168)
Lithuania	0.075	[0.055]	(0.058)	0.106*	[0.053]	(0.058)	0.086	[0.067]	(0.087)	0.117	[0.083]	(0.090)
Moldova	0.202***	[0.054]	(0.054)	0.195***	[0.053]	(0.056)	0.195***	[0.067]	(0.067)	0.185***	[0.061]	(0.067)
Poland	0.074**	[0.040]	(0.033)	0.074**	[0.041]	(0.050)	0.078**	[0.041]	(0.047)	0.022	[0.047]	(0.050)
Romania	0.004	[0.038]	(0.035)	0.040	[0.030]	(0.035)	0.008	[0.038]	(0.042)	0.001	[0.040]	(0.042)
Russia	0.054	[0.048]	(0.051)	0.082*	[0.048]	(0.048)	0.097	[0.053]	(0.061)	0.088	[0.056]	(0.070)
Serbia and Montenegro	-0.003	[0.043]	(0.051)	0.000	[0.038]	(0.044)	0.029	[0.046]	(0.055)	0.065	[0.049]	(0.057)
Slovak Republic	0.042	[0.045]	(0.051)	0.032	[0.055]	(0.056)	0.075	[0.073]	(0.072)	0.025	[0.060]	(0.078)
Slovenia	0.077	[0.069]	(0.061)	0.110	[0.071]	(0.059)	0.116*	[0.064]	(0.086)	0.028	[0.086]	(0.085)
Tajikistan	0.116*	[0.049]	(0.056)	0.031	[0.056]	(0.073)	0.078	[0.053]	(0.078)	0.070	[0.062]	(0.094)
Turkey	0.065**	[0.038]	(0.034)	0.012	[0.034]	(0.041)	0.040	[0.037]	(0.036)	0.007	[0.042]	(0.045)
Ukraine	0.064	[0.050]	(0.048)	0.053	[0.050]	(0.053)	0.024	[0.053]	(0.053)	0.008	[0.052]	(0.056)
Uzbekistan	0.009	[0.062]	(0.058)	0.074	[0.060]	(0.067)	0.046	[0.075]	(0.087)	0.115	[0.078]	(0.129)

The outcome variable is the employment share of workers with some university or higher education; the treatment indicator is the dummy for importing firms. Analytical and bootstrapped standard errors (based on 100 replications) are reported in square and round brackets, respectively. ***, **, *: indicate significance at the 1, 5, and 10% level, respectively.

Table A3 - Variables and Descriptive Statistics

Name	Definition	Obs.	Mean	Std. Dev.
Ind: Importer	Dummy equal to 1 if the firm imports any share of its inputs directly	14008	0.287	0.452
Share of workers with tertiary+ education	Employment share of workers with some university or higher education	13755	0.270	0.295
Ind: 50-249 empl (3 yrs bef)	Dummy equal to 1 if the firm had 50-249 employees three years before the survey	13566	0.195	0.396
Ind: 250+ empl (3 yrs bef)	Dummy equal to 1 if the firm had 250 or more employees three years before the survey	13566	0.109	0.311
Δlabor productivity (prev 3 yrs)	Percentage change in labor productivity (sales per worker) over the previous three years	13223	0.153	0.522
Δcapital intensity (prev 3 yrs)	Percentage change in capital intensity (fixed assets per worker) over the previous three years	13112	0.127	0.397
Δemployment (prev 3 yrs)	Percentage change in full-time employment over the previous three years	13787	0.004	0.108
Capacity utilization (3 yrs bef)	Level of utilization of facilities and man power three years before the survey	13636	0.792	0.211
Age	Year of the survey minus year in which the firm started operations in the country	14001	15.390	18.246
Ind: Uses ICT	Dummy equal to 1 if the firm regularly uses e-mail and internet in its interactions with clients and suppliers	14008	0.559	0.496
Ind: Exporter	Dummy equal to 1 if the firm exports any share of its output directly	13990	0.235	0.424
Ind: State owned	Dummy equal to 1 if 50% or more of the firm is owned by the government or a government agency	13944	0.108	0.310
Ind: Foreign owned	Dummy equal to 1 if 50% or more of the firm is owned by a foreign entity	13985	0.073	0.260
Ind: Privatized	Dummy equal to 1 if the firm was established from the privatization of a state-owned enterprise	14008	0.141	0.348
Ind: Faces significant import competition	Dummy equal to 1 if the firm declares import competition in its main market to be at least fairly important	13466	0.514	0.500
Ind: Competes on national mkt	Dummy equal to 1 if the firm competes on the national market for its main product	13759	0.720	0.449
Ind: Is credit constrained	Dummy equal to 1 if access to financing is a moderate or major obstacle to the firm's growth	13308	0.433	0.496
Ind: Has gvt among customers	Dummy equal to 1 if the firm sells 20% or more of its output to the government or a government agency	13523	0.129	0.335
Ind: Has MNEs among customers	Dummy equal to 1 if the firm sells 20% or more of its output to a multinational firm located in the country	13523	0.073	0.260
Ind: Received subsidies from ntl gvt (prev 3 yrs)	Dummy equal to 1 if the firm received any subsidy from the national government over the previous three years	13879	0.040	0.197
Ind: Received subsidies from loc gvt (prev 3 yrs)	Dummy equal to 1 if the firm received any subsidy from the regional or local government over the previous three years	13855	0.026	0.159
Price-cost margin	Percentage margin by which sales price exceeds operating costs in the main product line of the firm	12188	0.210	0.141
Ind: Has problems finding necessary skills	Dummy equal to 1 if finding necessary skills is a moderate or major obstacle to the firm's growth	13699	0.296	0.456
Weeks to fill a vacancy (white-collar)	Average number of weeks to fill out the most recent vacancy for white-collar jobs	14008	1.444	3.013
Weeks to fill a vacancy (blue-collar)	Average number of weeks to fill out the most recent vacancy for blue-collar jobs	14008	1.191	2.506
Ind: Develops a new product	Dummy equal to 1 if the firm develops successfully a major new product line or service	13984	0.357	0.479
Ind: Exports to a new country	Dummy equal to 1 if the firm exports to a new country	13302	0.119	0.323
Ind: Obtains quality accred	Dummy equal to 1 if the firm obtains a new quality accreditation (ISO 9000, 9002, 14000, AGCCP, etc.)	13963	0.129	0.335
Ind: Has positive expend in mktg	Dummy equal to 1 if the firm has positive expenditure in advertising and marketing	12372	0.433	0.496
Ind: Acquires new tech	Dummy equal to 1 if the firm acquires a new technology	13869	0.299	0.458
Ind: Performs R&D	Dummy equal to 1 if the firm performs Research and Development	12372	0.179	0.383