Immigrants and Firm Export Performance Across Destinations

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Abstract

This paper investigates the export-enhancing effect of immigrant workers at the firm-level and explores how this effect varies across occupations. We use a dataset of French manufacturing firms from 1997 to 2008 and address the problem of endogenous employment choice and selection bias using a propensity score matching estimation. Our results show that immigrants in both low- and high-skilled occupations foster exports at both extensive and intensive margins. This effect is spread over all export-destinations and goes beyond a destination-specific effect usually put forward in the literature.

Keywords: Exports, Firms, Heterogeneity, Immigrants

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1 Introduction

The export-enhancing effect of immigrants is usually related to the information they convey on their origin countries (Andrews et al., 2017; Hatzigeorgiou and Lodefalk, 2016; Parrotta et al., 2016; Hiller, 2013; Peri and Requena-Silvente, 2010). Existing firm-level studies show that immigrants possess valuable knowledge on foreign markets that decreases variable and fixed costs faced by exporters. Consequently, they foster exports at both extensive and intensive margins, especially with respect to their origin countries. This pro-trade effect is found to be larger for high-skilled workers, which is in line with the idea that high-skilled individuals are more likely to possess and gainfully apply information that is relevant for exporters.

Mitaritonna et al. (2017) suggest another mechanism through which immigrants may impact exports. Their complementarity with natives can lead to task reallocation and to more efficient technological choices. Hence, immigration increases the total factor productivity of firms. This productivity upgrade, in turn, increases exports at the intensive margin. Such export-enhancing effect of immigrants through productivity is not necessarily destination-specific.

In this paper we revisit the export-enhancing effect of immigrants and challenge the two aforementioned results of the literature. First, we investigate to what extent the effect holds across immigrants' occupations. Second, we test whether the effect is purely destination-specific or not. Specifically, we intend to address two major drawbacks of existing studies. First, only a limited number of papers address the presence of a reverse causality bias: foreign employment can very well be driven by the firm's export performance. Second, to the best of our knowledge, no paper tackles the selection bias: one can only observe the effect of immigrants on the firms that employ them.

We combine three datasets on French manufacturing firms over the 1997-2008 period. We identify foreign-born workers in a comprehensive matched employer-employee dataset that we further combine with trade data at the firm-destination level and balance sheet data at the firm level.[1] Our sample is made of 1,098,697 firms which engage in exports at least once over the 1997-2008 period.

We start by estimating the pro-trade effect of immigrant workers across occupations. To account for the reverse causality and selection biases, we estimate the trade-induced effect of immigrant workers with a propensity score matching (PSM) approach. It allows us to capture differences in exports stemming from differences in foreign employment. We find that both extensive and intensive margins positively react to the employment of immigrant workers. On average, a firm employing foreign-born workers exports 11.7% more in value and has a probability to export 0.4% higher than a control firm. This pro-trade effect is not restricted to immigrants in high-skilled occupations. Immigrants in low-skilled jobs are also associated with an export-enhancing effect, especially at the intensive margin. Firms employing high-skilled immigrants export 43.5% more in value than a control firm, and those employing low-skilled immigrants export 7.8% more in value than a control firm.

[1] Note that we do not have information on foreign-born workers' country of birth. The dataset in hands yet allows us to distinguish natives from foreign-born individuals.

We argue that the pro-trade effect of immigrants in low-skilled jobs cannot be explained by the informational channel which is generally emphasized in the literature for high-skilled immigrants, as these workers are less likely to occupy decision-making posts or to be in a position to transfer operative information about foreign markets to their employer. It could nonetheless be rationalized by a productivity-enhancing effect of immigrants put forward by the literature on complementarity in tasks (Peri and Sparber, 2009) and in the spirit of Mitaritonna et al. (2017).

To illustrate such an export-enhancing effect of immigrant workers that would be at play across occupations, we provide a short theoretical model of heterogeneous firms. We allow immigrant workers to impact firm-level exports through two different channels documented in the literature so far. We assume that immigrant workers convey valuable information on foreign markets which lowers trade costs. Furthermore, immigrant workers have a positive impact on total factor productivity through their complementarity with natives, consistent with a pro-trade effect of immigrant workers at both trade margins and regardless of their skill level or occupation.

In addition, our model predicts that immigrant workers foster exports beyond exports to their origin country. We exploit variations in exports across destinations so as to provide additional ground for the existence of a *non-destination-specific* effect of immigrant workers. Consistently with the theoretical model we provide, our results show that immigrants in both low- and high-skilled occupations increase exports to any destination. In a corollary exercise, we further show that they *do not* increase the concentration of exports across destinations.

The contribution of this paper is twofold. First, we put forward that immigrants in both low- and high-skilled jobs enhance exports at both intensive and extensive margins. We rationalise this result with a simple theoretical model of heterogeneous firms in which we describe an explicit link between foreign employment, productivity and exports. Available theoretical models have so far focused exclusively on the cost-decreasing effect of immigrants and these models leave no room for the empirical finding of a pro-trade effect of low-skilled immigrants. We infer from our model that the export-enhancing effect of immigrants is not necessarily destination-specific and our data show this to be empirically true.

Second, we depart from existing studies by proposing an alternative estimation strategy to insulate our results from both the reverse causality and selection biases. Most papers tend to address the endogeneity issues with an instrumental variable approach. While appropriate for the reverse causality bias, the instrumental variable approach does not accommodate the selection bias. Chosen in this study, the PSM approach enables us to explicitly control for the predisposition of firms to employ immigrant workers. To the best of our knowledge, our study is the first to attempt to do so.

The paper most closely related to ours is the study of Mitaritonna et al. (2017). As mentioned above, the authors explain their results on the productivity-enhancing effect of immigrants by appealing to the literature on complementarity in tasks. We follow this line of though, however, we depart from Mitaritonna et al. (2017) in two respects. First, their study deals with the consequences of a local immigration shocks on firm productivity and the subsequent effect on exports. We study the link between foreign employment and exports at the firm-level and test the implications of their results at a finer level of disaggregation. Second, Mitaritonna et al. (2017) focus on local immigration shocks pooling together the productivity effects of heterogeneous immigrants, disregarding whether they are workers or non-workers, high-skilled or low-skilled. We, however, only focus on immigrant workers and distinguish between low- and high-skilled-occupations.

The remainder of the paper is organized as follows. In the next section, we present the progress and shortcomings of the related literature. In Section 3, we present the French firm-level data used to estimate the pro-trade effect of immigrants. In Section 4, we present a first set of results supporting the export-enhancing effect of foreign-born workers derived from a PSM approach. In Section 5, we develop a theoretical framework rationalising the effect of immigrants on exports. We pursue our empirical analysis in Section 6 by providing further evidence that immigrant workers favour exports to many destinations. Section 7 concludes.

2 How immigrants foster exports

2.1 Immigrants and export know-how

Numerous papers provide aggregate evidence on the pro-trade effect of immigrants and link this effect directly to the information and knowledge that immigrants posses. The seminal paper of Gould (1994) and subsequent work surveyed by Rauch (2001) and Parsons and Winters (2014) highlight that immigrants convey information and promote trust between their home and host countries. Their social capital reduces transaction costs and fosters bilateral trade. Most studies suggest that immigrants exert a greatest pro-trade effect on differentiated goods for which the price fails to transmit relevant information. The literature also suggests a larger pro-trade effect of high-skilled and voluntary migrants as compared to low-skilled and forced migrants.

More recent studies use firm-level data to analyse how immigrants impact exports. Hiller (2013) shows that in order to access the knowledge embedded in immigrants, firms should indeed employ them. Using Danish data on the manufacturing sector, the author finds that foreign employment increases the exported volumes and shifts the composition of exports toward immigrants' origin countries. The local presence of immigrants, however, has only a limited impact on exports. To highlight causality, Hiller (2013) instruments foreign employment by the average number of immigrants from a given origin employed in other firms of the industry, or in other firms of the region.

Using the same data, Parrotta et al. (2016) investigate the causal effect of an increase in ethnic diversity on export outcomes at both margins. The authors measure diversity using differences in spoken languages across workers. They find that more diverse firms perform better on foreign markets along all extensive margin measures. These firms have a higher relational capital which translates into an increased ability to initiate, manage and expand international business. To control for endogeneity, they use a shift-share instrument and identify supply-driven diversity from exogenous changes in the local labour supply in the 1990's, *i.e.* they assume that firms do not impact local economic outcomes or the presence of a correlation between past and contemporaneous immigration.

Hatzigeorgiou and Lodefalk (2016) use Swedish data and find that immigrant workers – in particular high-skilled and recently arrived individuals – increase exports at both margins, especially for small firms, to their origin countries. To overcome endogeneity, they use a GMM estimator and instrument foreign employment by the average foreign employment in other firms or in other firms of the industry. To show that their instrument is valid, they present a Swedish business survey which indicates that hiring of immigrant workers is not endogenous to trade.

Andrews et al. (2017) provide evidence on the cost-decreasing effect of high-skilled immigrants at the firm-level for Germany. They find that senior immigrants have a stronger export-enhancing effect as they are more likely to hold managerial positions and to influence export decisions. The effect is stronger for exports toward the origin country of immigrant workers. In line with the literature, the authors instrument foreign employment by the local immigration stock which excludes the workers of the firm.

Theoretically, the effect of immigration on exports has been demonstrated in a study by Peri and Requena-Silvente (2010) using the model of Chaney (2008). The authors assume that immigrants lower both variable and fixed export costs. Thus, less productive firms that were below the productivity threshold to export, become able to enter the export market when employing immigrants. They conclude that the trade-enhancing effect of immigrants should take place at both margins and corroborate this prediction using Spanish data. Their theoretical model, however, does not accommodate the possibility that low-skilled immigrants foster exports.

2.2 Immigrants and productivity upgrade

A recent strand of the literature investigates how immigrants affect technology and the consequent allocation of jobs within and between firms. This literature, pioneered by Peri and Sparber (2009), highlights that natives and immigrants are imperfect substitutes, and that immigrants induce task specialization. This re-allocation of tasks generates productivity gains and prevents natives' wages to decrease due to immigration.

Other papers suggest that industries absorb immigration by adapting their technologies. Lewis (2011) looks at the impact of immigration on the use of new technologies in US manufactures. The author shows that the supply of low-skilled labour is positively related to the use of labour-intensive technologies by firms. Similarly, Gandal et al. (2004) study the impact of Russian immigration on Israeli wages. The authors suggest that a switch in production technology, such as skill-biased technological change, may have absorbed labour-supply shocks caused by Russian immigration.

In a recent paper, Mitaritonna et al. (2017) explicitly analyse the link between immigration and productivity gains. Using French firm-level data over the 1995-2005 period, they find that an increase in the local supply of immigrants increases total factor productivity of firms located in that area. This result is rationalized through the literature on complementarity in tasks (Peri and Sparber, 2009). They also show that this productivity upgrade is associated with larger exports. They instrument the local supply of immigrants by a shift-share instrument based on the spatial distribution of immigrants in 1990. The authors exclude the possibility that the spatial distribution of immigrants in 1990 could be correlated with changes in labour demand due to firm productivity shocks, showing that local economic outcomes are not impacted by individual firms.

Finally, the discussion would be incomplete without mentioning that immigration may very well have a negative impact on productivity. For instance, ethnic diversity can create linguistic and cultural frictions. Using Danish employer-employee data over 1995-2005, Parrotta et al. (2014) find evidence that the workforce diversity in ethnicity of a firm has a negative impact on its total factor productivity. They tackle reverse causality by constructing a shift-share instrument where the firm diversity is instrumented using the local diversity of the labour supply.

3 Data, statistics and preliminary estimates

3.1 The data

We combine three datasets containing information on French firms over 1997-2008 by using a unique firm administrative identifier (the SIREN number). Below we present details on each dataset.

Administrative employer-employee data

First, we use annual employee declarations of firms (*Déclarations Annuelles des Données Sociales*, DADS) containing exhaustive information on the employment of firms settled on the French mainland territory from 1997 to 2008. This administrative database is made of compulsory reports provided by each employer on the gross earning of its employees. All wage-paying individuals and legal entities established in France are required to file payroll declarations; only individuals employing civil servants are excluded from filing such declarations. The dataset is thus made of information at the firm-employee-year level.

This dataset allows us to identify foreign-born workers. More precisely, the *etranger* variable allows us to know whether an employee was born in France or in a foreign country. The dataset, however, does not contain information about the exact country of birth of the workers.[2] When the *etranger* variable is left empty, we assume that the worker was born in France. As the DADS data only contains information on nativity, naturalized individuals are included in the group of foreign-born individuals. We also have information on the socio-economic category of each worker. We combine this information with a classification of categories into white- and blue-collar occupations to identify immigrants in low- and high-skilled jobs (Bombardini et al., 2015).

[2] The DADS data allow us to distinguish two groups of immigrant workers: those born inside the European Union and others. In the remainder of the paper, we do not exploit that information because the group of workers born outside the EU is too broad. To use this group, one would need to assume that a worker born in Switzerland eventually has the same pro-trade impact than a worker born on another continent.

We aggregate this dataset at the firm-level and count, for each firm, the number of native and foreign-born workers for each skill category. After removing obvious outliers and extreme values, the mean characteristics of the DADS dataset are in line with the macro-level evidence. For instance, in 2006 in the *Ile-de-France* region, 13.6% of workers are foreign-born, while the partial 2006 census estimates that immigrants represent 12.9% of the working-age population. At the national level, foreign-born workers represent 7.49% of all workers, which is close to the estimates proposed by Brücker et al. (2013). The final sample is made of 21,157,647 firm-year observations that corresponds to an average of 2,000,000 firms per year.

The advantage of using firm-level data in our case is twofold. First, we rely on firm-level data to focus only on the working among the immigrant population. In contrast to census data, our dataset exhaustively covers the employment of immigrants in France. This dataset is thus appropriate for a consistent identification of the pro-trade effect of immigrant workers on exports within the firm boundaries. Using this dataset allows us to depart from existing studies which use regional immigration data to estimate the effect of immigration on the average local firm performance and can therefore contain externalities arising from the proximity to an immigrant population. Second, our dataset allows us to identify firm-level mechanisms which are undoubtedly more precise than those available at the aggregate level when it comes to capturing causal effects.

Customs trade data

We then use firm-level trade data from the French customs over the 1997-2008 period. This database reports the volume (in tons) and the value (in Euros) of exports for each CN8 product (European Union Combined Nomenclature at 8 digits) and destination, for each firm located on the French mainland territory. Some shipments are excluded from this data collection. Inside the EU, firms are required to report their shipments by product and destination country only if their annual export value exceeds the threshold of 150,000 Euros. For exports outside the EU, all flows are recorded unless their value is smaller than 1,000 Euros or one ton. Yet, these thresholds eliminate a very small share of the total French exports. From this dataset, we only keep merchandise shipments, excluding agricultural and services exports.

The dataset contains 26,186,006 observations at the firm-year-destination-product level, which we aggregate into 7,110,894 observations at the firm-year-destination level and into 1,381,500 observations at the firm-year level. Merging customs data with the DADS data leaves us with a dataset of 21,157,647 firm-year observations, of which 1,043,790 are exporters (representing 98% of total French exports) and 20,113,857 are non-exporters.

Balance-sheet data

We complete the picture using a balance-sheet dataset constructed from the reports of French firms to the tax administration over the 1997-2008 period (*Bénéfices Réels Normaux*, BRN). This dataset contains information on the value added, total sales, capital stock, debt structure and other variables at the firm level. This dataset excludes the agricultural and financial sectors.

Importantly, it contains both small and large firms, since no threshold applies on the number of employees for reporting to the tax administration.

We restrict our sample to manufacturing firms. The dataset contains between 550,000 and 650,000 firms per year (around 50% of the total number of French firms). In total, the dataset is made of 5,850,838 firm-year observations of which 5,351,632 can be merged into the sample of 21,157,647 firm-year observations. Depending on the year, these firms represent between 90% and 95% of French exports contained in the customs data.

3.2 Descriptive statistics

Our final sample contains 1,098,697 French manufacturers and 5,351,632 firm-year observations. We report a number of firm characteristics in Table 1. The sample includes small and large firms in terms of profit, financial resources and productivity. It includes both non-exporters (86%) and exporters (14%). These exporters ship about of 3,825 thousands of Euros and about 25 different products to an average of 6 destinations. French manufacturers employ about 96% of native and 4% of foreign-born workers. The share of foreign employment is low and approximately 74.21% of firms do not employ any immigrant worker. Finally, the share of workers in high-skilled occupations is higher among foreign-born workers (10.25%) than among native workers (9.26%).

We then focus on firm export performance measures in Table 2. We reports a number of statistics for firms employing no foreign-born worker and firms employing at least one foreign-born worker. We report whether the means across the two groups differ from zero in the last column. Firms employing immigrant workers exhibit export performance measures that are significantly higher. 16.3% of firms export among those employing immigrant workers, while only 13.2% of firms export among firms employing none. This trend holds along all extensive and intensive margin measures.

3.3 Foreign employment and export performance: Preliminary estimates

To investigates the link between firms' export performance measures and their employment of immigrant workers, we estimate the following linear probability model:

$$y_{it} = \mathrm{D}_{it} + \gamma_i + \gamma_{sr} + \gamma_{st} + \varepsilon_{it} \tag{1}$$

where y_{it} denotes the export performance of a firm i at time t, D_{it} is a dummy variable equal to one if the firm employs a positive number of immigrant workers at time t and γ_i, γ_{sr} and γ_{st} respectively denote firm, sector-region and sector-year fixed effects.

Firm fixed effects are included to control for time-invariant firm characteristics that affect the probability of employing immigrant workers. Sector-region fixed effects allows us to investigate variations in foreign employment within a local labour market. Sector-year fixed effects are included to account for unobserved heterogeneity in the employment of immigrant workers which may be favoured, possibly because of skill requirements, in one particular sector at a certain time.

We report the results in Table 3. We consider different export outcomes: the export value and the export quantity for the intensive margin; the number of destinations served, the number of HS6 products exported and the probability to export (participation dummy) for the extensive margin. We find that foreign employment has a positive and significant impact on the intensive margin measures (columns 1 and 4) as well as the extensive margin measures (columns 7, 10 and 13). This result holds across occupations, although the export-enhancing effect is slightly higher for immigrant workers in high-skilled occupations (columns 2, 5, 8, 11 and 14) as compared to immigrants in low-skilled occupations (columns 3, 6, 9, 12 and 15). We thus infer that the pro-trade effect of immigrants does not seem to be restricted to immigrants in high-skilled occupations. Causality may, however, be flawed by several endogeneity biases that we detail in the next section.

Table 1: Firm characteristics

	Obs.	Mean	Std. Dev.
Firm characteristics			
Profit (in thousands of Euros)	5,351,632	0.215	15.448
Revenue (in thousands of Euros)	5,351,632	6.014	597.472
Own resources (in thousands of Euros)	4,951,881	4.637	244.232
Assets (in thousands of Euros)	5,351,632	13.972	1,307
Capital intensity	4,846,312	82.512	2,299
Age (since creation)	4,715,348	16.112	13.251
Apparent labour productivity	5,942,550	60.913	6,688
Export performance			
Participation dummy	5,351,632	0.140	0.347
Export value (in thousands of Euros)	748,160	3,825	8.08e+07
Export quantity (in tons)	748,163	2,096,826	4.79e+07
No. of destinations	748,163	6.613	10.815
No. of exported products	748,163	25.638	111.780
Export concentration (Herfindahl index)	748,163	0.663	0.324
Employment			
Share of native workers	5,351,607	0.961	0.137
Share of immigrant workers	5,351,556	0.039	0.137
Employment across occupations			
Share of native workers in high-skilled jobs	5,351,607	0.089	0.231
Share of native workers in low-skilled jobs	5,351,607	0.871	0.261
Share of immigrant workers in high-skilled jobs	5,351,556	0.004	0.050
Share of immigrant workers in low-skilled jobs	5,351,556	0.035	0.126

Note: Capital intensity is measured by the fixed assets per employee. Apparent labour productivity is measured by the value added per employee. The participation dummy takes the value of one if the firm is an exporter at a given time, zero otherwise. The concentration of export across destinations is computed using a Herfindahl index.

Table 2: Export performance across foreign employment

	$\mathbf{M}_{it} = 0$			$\mathbf{M}_{it} > 0$			
	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.	Diff.
Participation dummy	4,441,652	0.132	0.339	909,980	0.163	0.369	a
Export value (in thousands of Euros)	586,874	3,551,951	6.19e+07	148,225	5,235,795	1.33e,+08	a
Export quantity (in tons)	586,874	2,048,694	4.97e+07	148,225	2,444,772	4.24e+07	b
No. of destinations	586,874	6.641	10.872	148,225	6.995	10.934	a
No. of exported products	586,874	25.419	108	148,225	28.490	127	a
Export concentration (Herfindahl index)	586,874	0.645	0.335	148,225	0.636	0.335	a

Note: The participation dummy takes the value of one if the firm is an exporter at a given time, zero otherwise. The concentration of export across destinations is computed using a Herfindahl index. M_{it} denotes the number of immigrant workers employed by firm i at time t. We test whether the means across the two groups differ from zero. a, b and c respectively denote significance at the 1%, 5% and 10% levels.

Table 3: Export performance and immigrant workers – OLS results

	Intensive margin						*Extensive margin*								
	Export value			Export quantity			No. of destinations			No. of products			Participation dummy		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
D_{it}	0.108^a			0.099^a			0.042^a			0.065^a			0.008^a		
	(0.006)			(0.007)			(0.002)			(0.003)			(0.000)		
D_{it}^{HS}		0.105^a			0.102^a			0.042^a			0.061^a			0.007^a	
		(0.010)			(0.012)			(0.004)			(0.005)			(0.001)	
D_{it}^{LS}			0.104^a			0.097^a			0.042^a			0.063^a			0.009^a
			(0.006)			(0.007)			(0.002)			(0.003)			(0.001)
Firm FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Sector-region FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Sector-year FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Obs.	675,572	675,572	675,572	680,151	680,151	680,151	687,898	687,898	687,898	687,898	687,898	687,898	5,197,867	5,197,867	5,197,867
R^2	0.863	0.862	0.863	0.874	0.873	0.873	0.877	0.877	0.877	0.874	0.874	0.874	0.755	0.755	0.755

Note: This table provides OLS estimates for the intensive and extensive margins. All trade margin measures are in logarithm, except the participation dummy. D_{it} , D_{it}^{HS} and D_{it}^{LS} respectively denote a dummy variable equal to 1 if the firm employs a positive number of immigrant workers in all, low- and high-skilled occupations. Standard errors, clustered at the sector-year level, are shown in parentheses. a, b and c respectively denote significance at the 1%, 5% and 10% levels.

4 The export-enhancing effect of immigrant workers

In this section, we estimate the export-induced effect of foreign-born workers at the firm level. We provide evidence that the pro-trade effect of foreign workers occurs at both trade margins and for both low- and high-skilled occupations. We first argue that our empirical strategy must account for endogeneity concerns and introduce the specifics of the PSM strategy that we have chosen. We then report our main findings, as well as the results of some robustness tests.

4.1 Endogeneity concerns

When estimating the trade impact of immigrant workers, one needs to consider the presence of a reverse causality bias. At the micro level, causality may run from firm performance to employment decisions with respect to natives and immigrants. We cannot exclude that firms may favour the employment of immigrant workers coming from the destinations with which they already have a trading experience (Choquette and Meinen, 2015; Minondo, 2011). More generally, the export performance of the firm may affect both its preference and its ability to attract a certain type of workers, and thus bias the estimation. These mechanisms generate a potential upward bias of the pro-trade effect of immigrant labour and challenge empirical findings that do not adequately address them.

So far, studies intending to tackle reverse causality have instrumented contemporaneous foreign employment using either the lagged immigration stocks, the regional and/or sectoral immigration stock or the immigration stock of a neighbouring country. Some studies rely on shift-share instruments *à la* Card (2001). Yet, to use lagged immigration stock, one needs to assume that the potential reverse causality is not time resistant. To use local immigration stock, one should assume that the local presence of immigrants is exogenous to the firm performance, while it has been shown that export-relevant information is not only individual-specific, but it is to some extend embedded in the population of immigrants (Parsons and Winters, 2014). To complicate matters further, Hatzigeorgiou and Lodefalk (2016) illustrate how aggregate and regional immigration stocks are inadequate proxies of foreigners employed in private businesses.

Another endogeneity concern relates to the presence of a selection bias: one can only observe the effect of immigrants on the firms that actually employ them. Put differently, even if we may observe that the firms employing immigrants actually benefit from such employment decision, firms employing none could face either gains or losses if they were to employ some. In other words, omitted variables that could increase exports but that are positively correlated with the employment of immigrant workers would induce an upward bias of the OLS estimates presented in Section 3. On the contrary, if these variables are negatively correlated with the employment of immigrants, OLS estimates would be downwardly biased. To the best of our knowledge, this selection bias has not yet been taken into account by the literature on immigrant labour and could generate either an upward or a downward bias of the estimated pro-trade effect of immigrants.

We implement a PSM approach to correct for the presence of both reverse causality and selection biases. As micro-level data availability in trade caught up somewhat with the data coverage and quality known in such fields as labour economics, this approach has become widespread in the estimation of causal treatment effects using observational data in trade literature.[3]

The advantage of this method, over a multivariate regression analysis such as the IV-2SLS framework, is to allow one to remain agnostic about the firm's decision to hire an immigrant worker. It allows us to overcome the fact that firms may have different probabilities to employ immigrant workers and that these probabilities may be correlated with their export performance. Moreover, PSM controls for the reverse causality bias when post-treatment characteristics are balanced. Finally, it enables us to take full advantage of the micro-level data by keeping all information on foreign employment at the firm level.

4.2 Propensity score matching and treatment effect estimations

To estimate the average treatment effect of employing foreign-born workers on export outcomes, we implement a PSM method. We build our strategy based on the guidance offered by Caliendo and Kopeinig (2008), Dehejia and Wahba (2002) and Stuart (2010)

Let D_{it} denotes a dummy variable which equals one if a firm i is *treated*, *i.e.* if it employs at least one immigrant worker at time t. Conversely, $D_{it} = 0$ for an *untreated* or a *control* firm i that employs no immigrant worker at time t.

Let X_{it}^T denotes the export outcome of firm i at time t when it is part of the treated group and X_{it}^C when it pertains to the control group. Summing over firms of each group, we are able to observe the following expected values:

$$E[X_{it}^T \mid D_{it} = 1] \tag{2}$$

$$E[X_{it}^C \mid D_{it} = 0] \tag{3}$$

The difference in equations (2) and (3) is made of the *average treatment effect on the treated* (ATT) and a sampling bias:

$$E[X_{it}^T \mid D_{it} = 1] - E[X_{it}^C \mid D_{it} = 0] = \text{ATT} + E\left(X_{it}^C \mid D_{it} = 1\right) - E\left(X_{it}^C \mid D_{it} = 0\right) \tag{4}$$

where:

$$\text{ATT} = E\left[X_{it}^T - \left(X_{it}^C \mid D_{it} = 1\right)\right] \tag{5}$$

We are interested in capturing this ATT. Yet, the ATT is not observable if the sampling bias is not nil. The sampling bias is the difference in outcomes that is attributable to differences in the treated and the control groups (such as different firm characteristics) rather than any effect of the treatment itself. An adjustment for any sampling bias would be straightforward if

[3]Initially, the PSM approach was used in the estimation of causal treatment effects stemming from a natural experiment (Rosenbaum and Rubin, 1983). It is now extensively used to analyse observational data in diverse fields of economics including labour economics and trade.

firms differed along a small set of (measurable) dimensions. This is not feasible, however, when comparing firms which vary across a wide number of dimensions.

The PSM method allows to overcome this challenge. This methodology matches treated firms to a subset of untreated firms based on a set of observable firm characteristics, denoted by vector C_{it} hereafter. Rosenbaum and Rubin (1983) show that it is sufficient to match treated and control observations based on a *propensity score*, denoted $p\left(C_{it}\right)$, which is a scalar variable representing the probability that a firm i receives the treatment at time t. The propensity score is given by the conditional probability of firm i to employ immigrant workers given pre-treatment characteristics:

$$p\left(C_{it}\right)=\operatorname{Prob}\left(D_{it}=1 \mid C_{it}\right) \tag{6}$$

In practice, we compute the scores by estimating the following equation:

$$D_{it}=\alpha C_{it}+\gamma_{i}+\gamma_{st}+\varepsilon_{it} \tag{7}$$

which includes firm (γ_i) and sector-year (γ_{st}) fixed effects. We include firm fixed effects to control for time-invariant firm characteristics that affect the probability to employ immigrant workers. For instance, we cannot exclude that multinational firms may behave differently from domestic-only firms about the choice of their labour force, resulting in different probabilities of employing immigrant workers. Also, we cannot exclude that some executive managers may discriminate between native and immigrant workers. Sector-year fixed effects are included to account for unobserved heterogeneity in the employment of immigrant workers across sectors at a certain time.

Since the dependent variable in equation (7) is a binary variable, standard practice consists in using a logit estimator. However, insofar as fixed effects are crucial here, we estimate equation (7) using a linear probability model (LPM) allowing us to add fixed effects. We check that the predictive values for the score do not depart from the (0,1) support. In all specifications, we find that the estimated score is out of the (0,1) range for less than 0.01% of the observations, which we then drop from the sample.

Once the propensity scores are estimated, we match each treated firm with the non-treated firm that has the closest propensity score. As standard in the literature, we match with replacement to ensure the highest matching quality as possible, such that a control firm can be matched to several treated firms. We then estimate the average treatment effect (equation 5) as follows:

$$\mathrm{ATT}=E\left[X_{it}^{T} \mid D_{it}=1, p\left(C_{it}\right)-X_{it}^{C} \mid D_{it}=0, p\left(C_{it}\right)\right] \tag{8}$$

Equation (8) gives the change in export outcomes due to the employment of immigrant workers, after controlling for selection bias in foreign employment. The identification comes from the differences in export outcomes between matched firms, that is between firms having very close probabilities to employ immigrant workers but which are actually different in that respect.

Finally, to assess the quality of the matching method and thereby the quality of the ATT estimate, we check that, on average and after matching, treated and control firms have similar characteristics. The balancing property ensures that the reverse causality bias has been controlled for.

4.3 Results

We estimate the ATT of employing immigrant workers on different export outcomes: the export value and the export quantity for the intensive margin; the number of destinations served, the number of HS6 products exported and the probability to export (participation dummy) for the extensive margin.

We start by estimating the probability to be treated – to employ a positive number of foreign-born workers at time t – for each firm-year observation. We estimate this probability following equation (7) and using a LPM. Covariates (C_{it}) include firm size proxies, financial characteristic variables and firm-level hierarchy measures. Specifically, in the administrative employer-employee dataset, each worker is assigned a CS1 code which is a 1-digit socio-economic category. We compute the firm-level count of 1-digit categories and the Herfindahl index of concentration of all workers in these categories. The results of this first-step estimation are presented in the Appendix, Table 7, column (1). We predict the propensity scores from this estimation.

We then match each treated firm with a control firm having the closest score and belonging to the same sector-region pair. That is, we investigate whether variations in foreign employment, within a local labour market, can be linked to different export outcomes. Baseline results are presented in Table 4, in which we report the estimated ATT and the standard errors in parentheses.

Column (1) shows that both margins of trade react positively and significantly to the treatment. At the intensive margin, firms employing immigrant workers export larger values and larger quantities. On average, a firm employing foreign-born workers exports 11.7% ($e^{0.111}$) more in value and 17.6% ($e^{0.162}$) more in volume over all its destinations, than a control firm having the same probability to employ immigrant workers but choosing not to. At the extensive margin, we estimate that firms employing immigrant workers export a larger set of products toward a larger set of destinations than firms that only employ native workers. The participation dummy is affected positively by foreign employment: treated firms have a probability to export 0.4% higher than control firms.

Table 4: Average treatment effect on treated - Baseline results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment (D_{it})	$\mathrm{M}_{it} > 0$	$\mathrm{M}_{it} > \mathrm{M}_{it-1}$	$\mathrm{M}_{it} > \mathrm{M}_{it-1}$ $\mathrm{M}_{it-1} > 0$	$\mathrm{M}_{it}^{HS} > 0$	$\mathrm{M}_{it}^{HS} > \mathrm{M}_{it-1}^{HS}$	$\mathrm{M}_{it}^{HS} > \mathrm{M}_{it-1}^{HS}$ $\mathrm{M}_{it-1}^{HS} > 0$	$\mathrm{M}_{it}^{LS} > 0$	$\mathrm{M}_{it}^{LS} > \mathrm{M}_{it-1}^{LS}$	$\mathrm{M}_{it}^{LS} > \mathrm{M}_{it-1}^{LS}$ $\mathrm{M}_{it-1}^{LS} > 0$
Propensity score estimator	LPM								
Matching algorithm	Closest neighbour								
Matching constraint	Sector-region								
	Intensive margin								
Export value	0.111^a	0.221^a	0.075^b	0.361^a	0.343^a	0.163	0.075^a	0.209^a	0.135^a
	(0.016)	(0.019)	(0.032)	(0.031)	(0.038)	(0.100)	(0.017)	(0.020)	(0.034)
Export quantity	0.162^a	0.238^a	0.099^b	0.293^a	0.288^a	-0.008	0.145^a	0.254^a	0.184^a
	(0.020)	(0.024)	(0.040)	(0.039)	(0.048)	(0.122)	(0.021)	(0.025)	(0.042)
	Extensive margin								
No. of destinations	0.019^a	0.086^a	0.012	0.123^a	0.119^a	0.022	0.004	0.086^a	0.027^c
	(0.007)	(0.008)	(0.013)	(0.013)	(0.016)	(0.042)	(0.008)	(0.008)	(0.014)
No. of products	0.051^a	0.131^a	0.033^c	0.168^a	0.168^a	0.052	0.032^a	0.127^a	0.065^a
	(0.009)	(0.011)	(0.018)	(0.018)	(0.022)	(0.057)	(0.009)	(0.011)	(0.020)
Participation dummy	0.004^a	0.013^a	0.003^b	0.018^a	0.020^a	-0.001	0.003^a	0.014^a	0.005^a
	(0.000)	(0.001)	(0.002)	(0.002)	(0.003)	(0.008)	(0.001)	(0.001)	(0.002)

Note: This table provides the ATT estimates for the five dependent variables. All trade margin measures are in logarithm, except the participation dummy. Propensity scores upon which the matching is made are computed using predictions from the estimation of equation (7). M_{it}, M_{it}^{HS} and M_{it}^{LS} respectively denote the number of foreign-born workers in all, high- and low-skilled occupations in firm i at time t. We match firms using the estimated propensity scores from the same sector-region. Robust standard errors are shown in parentheses. ^{a}, ^{b} and ^{c} respectively denote significance at the 1%, 5% and 10% levels.

To control for the quality of the matching method, we check that the post-matching groups have similar characteristics. In Appendix, Table 8, we present the average values of variables used to compute the scores for the treated and non-treated observations. We also present the relative bias measure to support that the inference made using propensity-score matching is valid (Austin, 2009). Table 8 suggests that treated firms are not different, on average, from control firms. This suggests that comparing firms along chosen dimension makes sense and supports the strategy consisting in attributing differences in export performance to the employment of immigrant workers. The balance property also ensures that the reverse causality has been accounted for by the PSM approach. All the results presented hereafter are based upon comparable post-matching group characteristics that are available upon request.

We then investigate the effect associated to alternative treatments. In the second column of Table 4, we present the ATT estimates of an increase in foreign employment between time $t-1$ and time t. Column (3) presents the estimated ATT of an increase in foreign employment between time $t-1$ and time t, conditional upon having a positive foreign employment at time $t-1$. Specifically, we investigate the pro-trade effect of an increased foreign employment and whether this effect is concentrated on the first immigrant worker hired. When a firm starts employing immigrant workers, all trade margins should be positively affected. On the contrary, when a firm already employs immigrant workers, the effect could be smaller or absent because it excludes the effect of the first immigrant worker employed.

We find clear-cut evidence supporting a pro-trade effect of an increase in foreign employment at any margin: all coefficients in column (2) are positive and statistically significant, suggesting that increasing foreign employment generates a pro-trade effect. However, when we control for previous foreign employment, in column (3), we find a smaller positive effect on the intensive margin and on the export participation. We also estimate that the number of destinations and the number of products exported are not affected by the additional foreign employment. We infer from this set of results that additional immigrant workers generate a positive but lower pro-trade effect as compared to the first immigrant worker employed by the firm.

We replicate the same estimations differentiating foreign-born workers in high- and low-skilled occupations to investigate whether the effect could be driven by high-skilled workers only. Results are presented in Table 4 in columns (4) to (9). Estimates suggest that immigrant in high-skilled jobs generate an export-enhancing effect that seems to be quantitatively larger as compared to immigrant in low-skilled jobs. Both trade margins are positively affected by the employment of high-skilled immigrants (column 4) and by an increase in the number of high-skilled immigrants (column 5). Looking at column (6), we find that the latter pro-trade effect is restricted to the first immigrant hired by the firm. We do not find evidence supporting a pro-trade effect, at any margin, of an increased foreign employment once conditioned upon positive previous foreign employment. By contrast, in columns (7) to (9), we estimate a significant and positive effect arising from the employment of immigrant workers in low-skilled jobs and this finding is not restricted to the first immigrant worker. Yet, this export-enhancing effect is smaller than for immigrant in high-skilled occupations.

We infer from this set of results that immigrants in both types of occupations are driving the average export-enhancing effect of foreign employment at the firm level. While our result on immigrants in high-skilled occupations are consistent with the idea of the informational channel documented in the literature, the pro-trade effect for immigrant in low-skilled jobs is not. These workers are indeed less likely to provide operational information on their origin countries that would translate into a decrease in export costs. Moreover, information does not seem to play a role here, as their pro-trade effect is not restricted to the first immigrant employee.

Finally, comparing the ATT estimates presented in columns (1), (4) and (7) of Table 4 to the OLS estimates presented in Table 3, we infer the presence of a downward bias of the pro-trade effect of immigrant workers which the PSM approach allows to correct.

4.4 Robustness tests

We perform a number of robustness checks to address potential bias and alternative mechanisms that could affect our estimation of the pro-trade effect of foreign employment. All robustness tests tend to confirm the existence of an export-enhancing effect of immigrants in both low- and high-skilled occupations at both trade margins. Results are reported in Appendix.

4.4.1 Additional constraints in the matching procedure

Matching per import growth quartile. We start by using an alternative matching procedure. We match treated and control firms within the same sector-region pair and that belong to the same contemporaneous import growth quartile. Firm choices about imported inputs, such as input sourcing or input costs, are known to affect firm performance and thus export outcomes. We cannot exclude that the pro-trade effect of foreign-born workers may occur through an import channel that would then affect export outcomes. Skilled immigrant workers especially could provide relevant information for importing. We exclude this potential channel in our estimation by matching treated and control firms upon the same import growth quartile during the year of the treatment.

Results are displayed in Appendix, Table 9. ATT estimates are very close to the baseline estimates. We find a pro-trade effect that resists to the inclusion of the firm's import growth. We estimate a positive pro-trade effect of employing immigrant workers and of increasing foreign employment. The pro-trade effect does not seem to be restricted to the first immigrant worker or to immigrants in high-skilled jobs. In addition, employing additional immigrants in high-skilled jobs is not associated to any trade effect at the extensive margin.

Matching per export growth quartile. We also match treated and untreated firms within the same sector-region pair and that belong to the same pre-treatment export growth quartile. We thus compare firms that were on the same export growth path before being treated, at time $t-1$. This strategy allows us to further control for the presence of a reverse causality bias. Note that as we condition the treatment upon pre-treatment export growth, we cannot estimate the impact of foreign employment on the export participation.

ATT results are displayed in Appendix, Table 10. All trade margins are significantly and positively associated to foreign employment and particularly high-skilled immigrants. In columns (2) and (3), we find that the estimated ATT of increasing foreign employment between time $t-1$ and time t has a positive and significant impact on both trade margins, even though additional immigrant workers are not associated to any trade effect. These results hold for immigrants in both high- and low-skilled occupations.

Within-year results. In the baseline specification, we estimate the impact of foreign employment on firm-year export performance measures. The total variation may however come from variations across firms for a given year and across years for a given firm. We now explicitly focus on the effect of variations in foreign employment across firms for a given year, by matching treated and control firms within the same sector-region-year triplet.

Table 11 in Appendix presents the estimation results for the same treatments as before but including this additional constraint into our matching procedure. Comparing the differences in the export performance of two matched firms in the same year, we find that all trade margins are positively affected by the employment of immigrant workers. The pro-trade effect of an increased foreign employment conditional upon a positive foreign employment in $t-1$, is now positive and significant regardless of immigrants' occupations (columns 3, 6 and 9).

4.4.2 Alternative propensity scores

Logit estimator for scores. We test the robustness of our results using an alternative estimator for the propensity scores. We estimate the probability to be treated using a logit estimator and excluding the structure of fixed effects due to computational difficulties resulting from the sample size. Using a logit estimator is the standard approach used to compute scores in the literature.

First-step estimation results are presented in Appendix, Table 7, column (2). The ATT estimates based on scores computed from a logit estimation are presented in Appendix, Table 12. We estimate similar patterns for the pro-trade effect of immigrant workers as in the baseline estimation. ATT estimates are, however, larger as compared to the baseline estimates. This can be explained by the omission of fixed effects in the estimation of the scores which results in imprecise predictions of the probability to be treated.

Scores with noise. We acknowledge that the PSM strategy allows us to control for the reverse causality because we assume that most of the factors driving the potential endogeneity bias can be observed. The richness of our dataset allows us to believe that selection on unobservables is negligible and that the PSM approach is adequate for causal inference. Nevertheless, to address the possibility that unobservables could introduce a bias in our estimation, we use the predicted scores computed using a linear probability model (Table 7, column 1) and multiply them by a random term distributed normally and ranging from zero to unity. In other words, we add noise to the scores which is equivalent to controlling for the omission of an unobserved variable in the computation of the scores.

The ATT estimates based upon these scores are presented in Appendix, Table 13. We estimate similar patterns for the pro-trade effect of immigrant workers as in the baseline estimation although the magnitude of the ATT estimates is clearly overestimated.

4.4.3 Alternative matching procedures

5-neighbour matching algorithm. We then use an alternative matching algorithm that consists in matching each treated firm with its five non-treated closest neighbours in propensity scores. ATT results are displayed in Appendix, Table 14. Baseline coefficients are confirmed, but the precision is slightly lower compared to the baseline estimates.

Closest neighbor and no replacement. We finally match treated and control firms with no replacement, instead of matching with replacement, such that a control firm can only be matched to one treated firms. ATT results are displayed in Appendix, Table 15. Both economic and statistical significance of the ATT estimates are confirmed but coefficients seems overestimated which can be understood by the lowers the quality of the matching when avoiding replacement.

5 Insights from a model of heterogeneous firms

In this section, we complement our empirical results with a model of heterogeneous firms *à la* Melitz (2003) to formalise the different channels through which an exogenous increase in foreign employment impacts the choice of a firm to serve a foreign market and the quantity it supplies.

5.1 Model set-up

Consider a world with $n+1$ symmetric countries open to trade: a domestic country denoted d and n foreign countries indexed by j. In each country, a continuum of firms operates under monopolistic competition and produces using a single input factor denoted L. Each firm faces the following demand function on each market:

$$q \quad = \quad Q\left(\frac{p}{P}\right)^{-\sigma} \tag{9}$$

where σ denotes the elasticity of substitution between any two varieties, p is the price of the firm variety, Q is the aggregate set of varieties consumed as an aggregate good and P is the associated aggregate price.

Each country is endowed with a stock of input factor made of native workers $\left(L^d\right)$ and foreign-born workers (L^i) and given by $L = \lambda\left(L^d, L^i\right)$. The input factor is paid at its marginal productivity which is equal to unity to ensure factor price equalization among countries.

5.2 Foreign employment and productivity

The firm size is given by $l = \lambda\left(l^d, l^i\right)$ where l^d and l^i respectively denote the number of native and foreign-born workers. l^d and l^i are randomly drawn from independent distribution functions.

Let φ denotes the firm productivity and be an increasing function of its size such that $\partial\varphi/\partial l \geq 0$. Firms are thus heterogeneous in size, which generates heterogeneity in productivity.

To understand the relationship between foreign employment and productivity, let us consider two cases. In the first case, immigrant workers have a positive marginal product ($\partial l/\partial l^i \geq 0$). Thus, a marginal increase in foreign employment has a positive impact on productivity. The mechanism at play is the following: an increase in foreign employment enables the firm to reach a larger size *i.e.* a higher isoquant in the economic region defined by function λ.

In the second case, immigrant workers have a negative marginal product ($\partial l/\partial l^i < 0$). Thus, a marginal increase in foreign employment has a negative impact on productivity. For instance, the cost to hire an additional immigrant worker in terms of necessary adjustments to accommodate language or cultural differences could be so high that it would penalise the efficiency of the firm workforce and lower its productivity. Here, an increase in foreign employment moves the firm into a lower size category. In other words, the firm relocates in the uneconomic region as defined by function λ, where isoquants are either upward-sloping or backward-bending.

Following available evidence, we specify function λ as a CES aggregate made of native and immigrant workers who are imperfect substitutes. In that case, the firm size is given by:

$$l = \left[\theta^d \left(l^d\right)^{\frac{\delta-1}{\delta}} + \theta^i \left(l^i\right)^{\frac{\delta-1}{\delta}}\right]^{\frac{\delta}{\delta-1}} \tag{10}$$

where θ^d and θ^i denote the group-specific productivity levels and δ is a positive constant denoting the elasticity of substitution between the two groups of workers. Using a CES function, the marginal product of each input factor is always positive ($\partial l/\partial l^d \geq 0$ and $\partial l/\partial l^i \geq 0$). This specification therefore excludes the case where $\partial l/\partial l^i < 0$. This is in line with the literature showing that immigrant workers increase productivity due to their imperfect complementary in tasks with native workers (Peri and Sparber, 2009).

5.3 Export to market j

The firm technology to serve a foreign market j is given by:

$$c_j = \frac{\tau_j}{\varphi} q_j + f_j \tag{11}$$

where τ_j denotes an iceberg cost and f_j denotes a positive fixed cost. Both export costs are firm- and destination-specific, thus the firm may not export toward all foreign destinations.

We consider that immigrant workers, especially immigrants in decisional and operative jobs, decrease export costs toward destination j, so that $\partial\tau_j/\partial l^i \leq 0$ and $\partial f_j/\partial l^i \leq 0$. In line with empirical evidence, we assume that immigrant workers provide operational information about their origin country, which eventually allows their firm to overcome trade barriers for that particular destination. We also consider that immigrant workers have a general knowledge of foreign markets that allows them to lower export costs toward other destinations. Finally, we account for non-linearities in the effect of foreign employment by allowing these derivatives to equal zero. This implies that the information brought by the first-hired immigrant worker may be more important than the information brought by the second one.

Profit maximization gives the quantity offered by the firm on market j:

$$q_j = Q\left[P\left(\frac{\sigma-1}{\sigma}\right)\frac{\varphi}{\tau_j}\right]^{\sigma} \tag{12}$$

and its *ex-post* profit:

$$\pi_j = \frac{R}{\sigma}\left[P\left(\frac{\sigma-1}{\sigma}\right)\frac{\varphi}{\tau_j}\right]^{\sigma-1} - f_j \tag{13}$$

5.4 Comparative statics

We now look at the emergence of first-order selection effects.[4] We consider that firms are small enough to have no impact on the general equilibrium, which allows us to study whether differences in foreign employment induce differences in export behaviours or not. The theoretical predictions of the model detailed hereafter are summarized in Table 5. The model predicts that two firms which *only* differ in their foreign employment exhibit different export outcomes at both margins.

Table 5: Impacts of immigrant workers on export performance

	Productivity $\partial\varphi/\partial\lambda$	Iceberg cost $\tau_j/\partial\lambda$	Fixed cost $f_j/\partial\lambda$
Extensive margin			
$\mathrm{d}\Pr(\pi_j \geq 0)/\mathrm{d}\lambda$	+	+	+
Intensive margin			
$\partial q_j/\partial\lambda$	+	+	0

Proposition. The profit realized on a foreign market j is given by $\pi_j\left(l^d, l^i\right)$. Due to the existence of a positive entry cost on market j (f_j), the zero-profit condition implicitly defines a firm-specific threshold function for market j as a function of l^d and l^i.

Result for the extensive margin. Given that foreign employment has a nil or positive impact on productivity, the higher the employment of immigrant workers, the higher the probability to enter market j:

$$\frac{\partial\pi_j}{\partial l^i} = \frac{\sigma-1}{\sigma}R\left[P\left(\frac{\sigma-1}{\sigma}\right)\right]^{\sigma-1}\left(\frac{\varphi}{\tau_j}\right)^{\sigma-2}\frac{1}{(\tau_j)^2}\left(\frac{\partial\varphi}{\partial l^i}\tau_j - \frac{\partial\tau_j}{\partial l^i}\varphi\right) - \frac{\partial f_j}{\partial l^i} \geq 0 \tag{14}$$

[4] We are able to study first-order selection effects because we assume that a general equilibrium exists and because the profit is continuous and decreasing in the marginal cost (Mrázová and Neary, Forthcoming). Mrázová and Neary (Forthcoming) explain that an equilibrium exist in any general model of monopolistic competition. This is likely to be the case for our framework since its structure is similar to the seminal model of Melitz (2003).

A marginal increase in the share of immigrant workers induces an increase in the firm productivity and a decrease in its variable and fixed export costs to market j.

Result for the intensive margin. Given that foreign employment has a nil or positive impact on productivity, the higher the employment of immigrant workers, the higher the exported quantity toward market j:

$$\frac{\partial q_j}{\partial l^i} = \sigma Q \left[P\left(\frac{\sigma-1}{\sigma}\right)\right]^{\sigma}\left(\frac{\varphi}{\tau_j}\right)^{\sigma-1}\frac{1}{(\tau_j)^2}\left(\frac{\partial\varphi}{\partial l^i}\tau_j - \frac{\partial\tau_j}{\partial l^i}\varphi\right) > 0 \tag{15}$$

A marginal increase in the share of immigrant workers entails an increase in the firm productivity and a decrease in its variable export cost to market j.

Our theoretical framework predicts that immigrant workers favour exports at both margins. Thanks to a productivity-enhancing effect, this effect is compatible with the existence of positive effects from immigrants in both low- and high-skilled occupations. Finally, the model establishes that, in addition to the destination-specific information provided by immigrant workers, a non-destination specific effect is at play. Foreign employment should therefore impact exports not only to their origin country, as broadly documented in the literature, but to any export destination.

6 Beyond the destination-specific effect of immigrant workers

To fully explore the consistency of the theoretical model with empirically observed patterns, we now investigate whether an increase in foreign employment fosters exports to any destination for a given firm. To do so, we use additional information from the customs dataset. To provide further support to the pro-trade effect of immigrant workers at the intensive margin, we exploit variations in exports across destinations for a given firm-year observation. Our dataset is now made of firm-destination-year observations.

Importantly, it allows us to investigate whether the effect of immigrant workers on exports is only destination-specific or not. Variations in exports across destinations are informative on whether foreign-born workers favour exports toward all destinations, or whether they skew exports toward a smaller set of countries. The latter result would only be consistent with an informational effect of immigrant workers.

This additional dimension of the data also helps to address some potential compositional effects that may affect our measure of the pro-trade effect at the intensive margin presented in Section 4. The firm-year export value may be flawed by an aggregation bias across destinations. Consider a firm exporting a given value to a foreign market j at time $t-1$. At time t, the firm exports the same value to market j, and enters a foreign market h. Due to export aggregation, both trade margins are affected at time t, while exports to market j remain constant. Using firm-destination information circumvents this potential bias.

6.1 Controlling for firm-destination-year shocks in exports

A robust measure of the intensive margin requires to control for firm-destination-year shocks in exports, such as firm entry, firm exit and changes in the destination portfolio of the firm. By purging firm-destination-year exports from idiosyncratic shocks at the firm, destination, year, firm-destination and destination-year level, we can recover variations that are common across destinations for a given firm-year observation which measures more carefully the intensive margin.

We estimate the following equation with an OLS estimator:

$$X_{ijt} = \gamma_i + \gamma_j + \gamma_t + \gamma_{it} + \gamma_{ij} + \gamma_{jt} + \epsilon_{ijt} \tag{16}$$

where X_{ijt} is the exported value by a firm i toward a destination j at time t, and is decomposed into γ_i, γ_j, γ_t, γ_{it}, γ_{ij} and γ_{jt} that respectively denote firm, destination, year, firm-year, firm-destination and destination-year fixed effects. We recover the estimated firm-year variation ($\hat{\gamma_{it}}$). We then estimate the ATT of foreign employment on this estimated firm-year fixed effect.

If the pro-trade effect of immigrant workers were to be solely driven by a destination-specific effect, variations at the intensive margin would be absorbed by the destination, firm-destination or destination-year fixed effects. On the contrary, a positive effect of foreign employment on the estimated firm-year fixed effect would support that variations are driven by changes in export flows in many destinations simultaneously. We would then infer that immigrant workers generate an export-enhancing effect common to many destinations.

Table 6 provides the ATT estimates of the different treatments on the estimated firm-year fixed effect ($\hat{\gamma_{it}}$). In the first line, we estimate a significant export-enhancing effect of immigrant workers on the estimated firm-year variations. We interpret this result as further evidence that foreign employment increases exports toward all destinations on average. If the destination-specific effect alone were at play, the estimated ATT would be driven to zero. On the contrary, we find that the coefficients for all treatments are significant and positive. We thus confirm the results presented in Section 4 showing that the export-enhancing effect of immigrant workers also occurs at the intensive margin. The quality of the matching procedure for the first ATT estimate of column (1) can be inferred from the first set of columns in Table 17 (in Appendix) and suggests comparable post-matching characteristics for both groups of firms.

We then corroborate the theoretical predictions presented in Section 5 showing that a non-destination-specific effect is at play for both high- and low-skilled immigrants, which is consistent with a productivity-enhancing effect. Table 16 presented in Appendix also provides the estimated ATT for each robustness test presented in section 4.4. All coefficients are positive and quantitatively close to baseline estimates.

Finally, we compare the ATT estimates presented in columns (1), (4) and (7) of Table 6 to the OLS estimates presented in Table 18 (in Appendix). We infer the presence of an upward bias for the export diversification effect of immigrant workers in high-skilled occupations, while we infer a downward bias for the effect of immigrants in low-skilled occupations.

Table 6: Average treatment effect on treated - Beyond the destination-specific effect of immigrant workers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment (D_{it})	$\mathrm{M}_{it} > 0$	$\mathrm{M}_{it} > \mathrm{M}_{it-1}$	$\mathrm{M}_{it} > \mathrm{M}_{it-1}$ $\mathrm{M}_{it-1} > 0$	$\mathrm{M}_{it}^{HS} > 0$	$\mathrm{M}_{it}^{HS} > \mathrm{M}_{it-1}^{HS}$	$\mathrm{M}_{it}^{HS} > \mathrm{M}_{it-1}^{HS}$ $\mathrm{M}_{it-1}^{HS} > 0$	$\mathrm{M}_{it}^{LS} > 0$	$\mathrm{M}_{it}^{LS} > \mathrm{M}_{it-1}^{LS}$	$\mathrm{M}_{it}^{LS} > \mathrm{M}_{it-1}^{LS}$ $\mathrm{M}_{it-1}^{LS} > 0$
Propensity score estimator	LPM								
Matching algorithm	Closest neighbour								
Matching constraint	Sector-region								
$\hat{\gamma}_{it}$	0.069^a	0.097^a	0.105^a	0.155^a	0.151^a	0.136^a	0.045^a	0.092^a	0.098^a
	(0.012)	(0.014)	(0.022)	(0.019)	(0.024)	(0.059)	(0.012)	(0.014)	(0.024)
Export concentration	-0.003	-0.016^a	0.003	-0.025^a	-0.027^a	-0.001	0.000	-0.017^a	-0.001
	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)	(0.011)	(0.002)	(0.002)	(0.004)

Note: This table provides the ATT estimates for the predicted firm-year fixed effect ($\hat{\gamma}_{it}$) from equation (16) and for the Herfindahl index of concentration of exports for a given firm-year. Propensity scores upon which the matching is made are computed using predictions from the estimation of equation (7). M_{it}, M_{it}^{HS} and M_{it}^{LS} respectively denote the number of foreign-born workers in all, high- and low-skilled occupations in firm i at time t. Robust standard errors are shown in parentheses. ^{a}, ^{b} and ^{c} respectively denote significance at the 1%, 5% and 10% levels.

6.2 Corollary: Concentration of exports across destinations

To support the prevalence of a non-destination-specific effect of immigrant workers, we now estimate the ATT of foreign employment on the concentration of exports (using a Herfindahl index) across destinations for a given firm-year observation. Our previous results suggest that immigrant workers tend to increase exports toward all destinations. Hence immigrant workers should *not* increase the concentration of exports. We would expect the latter effect to arise if immigrant workers only had a destination-specific pro-trade effect.

The second line of Table 6 provides the estimated ATT of the different treatments on the firm-year Herfindahl index of exports. No specification shows a positive and significant impact of foreign employment on the concentration of exports. We rather find that firms employing immigrant workers always exhibit a lower concentration of exports than the control firms. We interpret this as evidence in favour of a non-destination-specific effect of foreign employment on the intensive margin of trade. The quality of the matching procedure for the second ATT estimate of column (1) can be inferred from the second set of columns in Table 17 (in Appendix) and suggests comparable post-matching characteristics for both groups of firms.

Table 6 also shows that this result holds for immigrants in both high- and low-skilled occupations. All in all, this set of results supports that employing immigrant workers, disregarding of their occupation level, favours exports toward all destinations served by the firm. Results for each robustness test are presented in Appendix, Table 19 and corroborate these findings.

Finally, a comparison of Tables 6 and 18 (in Appendix) shows the presence of an upward bias of the export concentration effect of immigrant workers in high-skilled occupations, and a downward bias of the effect of immigrants in low-skilled occupations.

7 Conclusion

This paper investigates the export-enhancing effect of foreign employment at the firm level. Using a dataset on French manufacturing firms over the 1997-2008 period, we implement a propensity score matching method to evaluate the effect of immigrant workers on export outcomes. We find a positive effect of foreign-born workers on the export value, the export volume, the number of destinations served, the number of exported products and the probability of exporting. In line with the literature, we find that the export-enhancing effect is stronger for immigrants in high-skilled occupation. We, however, also find a robust and significant pro-trade effect of immigrants in low-skilled jobs that cannot be explained by the informational effect documented in the literature.

We complement our empirical study with a model of heterogeneous firms in monopolistic competition. We show that immigrant workers allow their firm to be more productive and provide valuable information about foreign markets to their employers. The model predicts that the probability to export and the exported quantity are positively affected by the employment of immigrant workers. Importantly, this effect holds for immigrants in both low- and high-skilled occupations. This illustrative model also predicts that foreign employment fosters exports to any destination and not simply to the countries of origin. We support this prediction with our data and show that this result holds across occupations, thus confirming the idea that productivity effects may be at play.

These results are quite instructive for further research on the link between foreign employment and export outcomes. Besides looking at the relationship between foreign employment and productivity (Mitaritonna et al., 2017), a promising research avenue could be to investigate further how foreign and native workers differ in terms of job preferences and the contracts they hold. It would help to better understand the causal link between foreign employment, efficiency (productivity, labour flexibility, etc.) and export outcomes.

Finally, our results suggest that employing either high- or low-skilled immigrants is at worst harmless and at best positive for export outcomes. In that respect, simplifications of labour regulations for immigrant workers including low-skilled immigrants could create further incentives for French firms to hire these workers. This could, in turn, create favourable conditions within the employing firm to start exporting or to expand its export activities.

In the current European context, policy makers should bear in mind that a tightening of immigration policies and labour regulations for immigrants may impact firm export outcomes. At the extensive margin, firms may experience a loss of opportunities to start exporting. At the intensive margin, one could expect a negative impact on exports. If these restrictions target immigrants from a particular origin country, the effect may be unevenly spread across export destinations, and could even lead to the redistribution of existing export flows toward a more restrictive set of destinations.

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Appendix

Table 7: Propensity score estimations

Dependent variable: $D_{it} = 1$ if $M_{it} > 0$	(1)	(2)
(log) Mean age of workers	0.023^a	0.078^a
	(0.000)	(0.007)
(log) No. of CS1	0.287^a	2.840^a
	(0.004)	(0.008)
Herf. CS1	0.160^a	2.088^a
	(0.003)	(0.011)
(log) Firm age	-0.000	-0.041^a
	(0.992)	(0.002)
(log) Employment	0.015^a	0.282^a
	(0.000)	(0.002)
(log) Assets	0.017^a	-0.102^a
	(0.000)	(0.002)
(log) Own resources	0.600	-2.214
	(0.466)	(1.212)
Firm FE	yes	no
Sector-year FE	yes	no
Obs.	3,871,637	3,988,933
Estimator	LPM	Logit
R^2	0.550	0.074

Note: This table provides the first-step estimation results allowing us to compute the scores (equation 7). The dependent variable denoted D_{it} equals one if $M_{it} > 0$ and zero otherwise. M_{it} denotes the number of foreign-born workers in firm i at time t. All independent variables are lagged $(t-1)$. In column (1), we use a linear probability model and include a set of fixed effects. In column (2), we use a logit estimator. Robust standard errors are shown in parentheses. a, b and c respectively denote significance at the 1%, 5% and 10% levels.

Table 8: Matching quality - Baseline results

Treatment (D_{it})	$M_{it} > 0$		
Propensity score estimator	LPM		
Matching algorithm	Closest neighbour		
Matching constraint	Sector-region		
	Treated	Control	% bias
(log) Mean age of workers	3.615	3.621	-2.7
(log) No. of CS1	1.293	1.266	8.7
Herf. CS1	0.645	0.648	-1.6
(log) Firm age	2.793	2.805	-1.7
(log) Employment	2.994	2.974	1.4
(log) Assets	7.922	7.967	-2.9
(log) Own resources	0.094	0.094	-2.0

Note: This table provides the observed means of firm characteristics (C_{it}) for the treated and the control groups after score matching and computation of the ATT on the (log) export value (Table 4). All variables are lagged ($t-1$). M_{it} denotes the number of foreign-born workers in firm i at time t. We compare the two means using a relative bias measures, relating the quality of the matching procedure. *% bias* denotes the normalized relative bias between the two means (Austin, 2009).

Table 9: Average treatment effect on treated - Matching per import growth quartile

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment (D_{it})	$\mathrm{M}_{it} > 0$	$\mathrm{M}_{it} > \mathrm{M}_{it-1}$	$\mathrm{M}_{it} > \mathrm{M}_{it-1}$ $\mathrm{M}_{it-1} > 0$	$\mathrm{M}_{it}^{HS} > 0$	$\mathrm{M}_{it}^{HS} > \mathrm{M}_{it-1}^{HS}$	$\mathrm{M}_{it}^{HS} > \mathrm{M}_{it-1}^{HS}$ $\mathrm{M}_{it-1}^{HS} > 0$	$\mathrm{M}_{it}^{LS} > 0$	$\mathrm{M}_{it}^{LS} > \mathrm{M}_{it-1}^{LS}$	$\mathrm{M}_{it}^{LS} > \mathrm{M}_{it-1}^{LS}$ $\mathrm{M}_{it-1}^{LS} > 0$
Propensity score estimator	LPM								
Matching algorithm	Closest neighbour								
Matching constraint	Sector-region-import growth quartile								
	Intensive margin								
Export value	0.137^a	0.158^a	0.120^a	0.315^a	0.230^a	0.167	0.109^a	0.132^a	0.101^a
	(0.020)	(0.023)	(0.037)	(0.034)	(0.042)	(0.106)	(0.020)	(0.024)	(0.039)
Export quantity	0.200^a	0.163^a	0.161^a	0.227^a	0.174^a	0.011	0.208^a	0.160^a	0.160^a
	(0.025)	(0.029)	(0.047)	(0.043)	(0.053)	(0.135)	(0.131)	(0.031)	(0.050)
	Extensive margin								
No. of destinations	0.036^a	0.057^a	0.020	0.111^a	0.079^a	0.005	0.026^a	0.053^a	0.027
	(0.008)	(0.010)	(0.016)	(0.015)	(0.018)	(0.045)	(0.009)	(0.010)	(0.017)
No. of products	0.075^a	0.089^a	0.045^b	0.147^a	0.119^a	0.032	0.062^a	0.092^a	0.060^a
	(0.011)	(0.013)	(0.022)	(0.020)	(0.024)	(0.061)	(0.012)	(0.014)	(0.023)
Participation dummy	0.008^b	0.008^a	0.001	0.017^a	0.009	-0.008	0.008^a	0.010^a	0.002
	(0.003)	(0.003)	(0.005)	(0.005)	(0.006)	(0.013)	(0.003)	(0.003)	(0.007)

Note: This table provides the ATT estimates for the five dependent variables. All trade margin measures are in logarithm, except the participation dummy. Propensity scores upon which the matching is made are computed using predictions from the estimation of equation (7). M_{it}, M_{it}^{HS} and M_{it}^{LS} respectively denote the number of foreign-born workers in all, high- and low-skilled occupations in firm i at time t. We match firms using the estimated propensity scores from the same sector-region and that belong to the same contemporaneous import growth quartile. Robust standard errors are shown in parentheses. ^{a}, ^{b} and ^{c} respectively denote significance at the 1%, 5% and 10% levels.

Table 10: Average treatment effect on treated - Matching per export growth quartile

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment (D_{it})	$\mathrm{M}_{it} > 0$	$\mathrm{M}_{it} > \mathrm{M}_{it-1}$	$\mathrm{M}_{it} > \mathrm{M}_{it-1}$ $\mathrm{M}_{it-1} > 0$	$\mathrm{M}_{it}^{HS} > 0$	$\mathrm{M}_{it}^{HS} > \mathrm{M}_{it-1}^{HS}$	$\mathrm{M}_{it}^{HS} > \mathrm{M}_{it-1}^{HS}$ $\mathrm{M}_{it-1}^{HS} > 0$	$\mathrm{M}_{it}^{LS} > 0$	$\mathrm{M}_{it}^{LS} > \mathrm{M}_{it-1}^{LS}$	$\mathrm{M}_{it}^{LS} > \mathrm{M}_{it-1}^{LS}$ $\mathrm{M}_{it-1}^{LS} > 0$
Propensity score estimator	LPM								
Matching algorithm	Closest neighbour								
Matching constraint	Sector-region-export growth quartile								
	Intensive margin								
Export value	0.135^a	0.215^a	0.158^a	0.423^a	0.390^a	0.265^a	0.108^a	0.213^a	0.105^a
	(0.016)	(0.020)	(0.033)	(0.029)	(0.039)	(0.099)	(0.016)	(0.020)	(0.034)
Export quantity	0.190^a	0.245^a	0.189^a	0.352^a	0.317^a	0.065	0.186^a	0.263^a	0.185^a
	(0.021)	(0.026)	(0.042)	(0.038)	(0.049)	(0.121)	(0.022)	(0.027)	(0.044)
	Extensive margin								
No. of destinations	0.023^a	0.084^a	0.030^b	0.147^a	0.128^a	0.050	0.015^b	0.073^a	0.016
	(0.007)	(0.009)	(0.014)	(0.013)	(0.017)	(0.043)	(0.007)	(0.009)	(0.015)
No. of products	0.056^a	0.126^a	0.056^a	0.202^a	0.180^a	0.087	0.047^a	0.120^a	0.045^b
	(0.009)	(0.012)	(0.019)	(0.018)	(0.023)	(0.058)	(0.010)	(0.012)	(0.020)

Note: This table provides the ATT estimates for the five dependent variables. All trade margin measures are in logarithm, except the participation dummy. Propensity scores upon which the matching is made are computed using predictions from the estimation of equation (7). M_{it}, M_{it}^{HS} and M_{it}^{LS} respectively denote the number of foreign-born workers in all, high- and low-skilled occupations in firm i at time t. We match firms using the estimated propensity scores from the same sector-region and that belong to the same quartile of pre-treatment export growth. Robust standard errors are shown in parentheses. ^{a}, ^{b} and ^{c} respectively denote significance at the 1%, 5% and 10% levels.

Table 11: Average treatment effect on treated - Within-year results

Treatment (D_{it})	(1) $M_{it} > 0$	(2) $M_{it} > M_{it-1}$	(3) $M_{it} > M_{it-1}$, $M_{it-1} > 0$	(4) $M_{it}^{HS} > 0$	(5) $M_{it}^{HS} > M_{it-1}^{HS}$	(6) $M_{it}^{HS} > M_{it-1}^{HS}$, $M_{it-1}^{HS} > 0$	(7) $M_{it}^{LS} > 0$	(8) $M_{it}^{LS} > M_{it-1}^{LS}$	(9) $M_{it}^{LS} > M_{it-1}^{LS}$, $M_{it-1}^{LS} > 0$
Propensity score estimator	LPM								
Matching algorithm	Closest neighbour								
Matching constraint	Sector-region-year								
	Intensive margin								
Export value	0.103^a	0.252^a	0.206^a	0.462^a	0.514^a	0.442^a	0.063^a	0.241^a	0.209^a
	(0.015)	(0.019)	(0.032)	(0.028)	(0.038)	(0.097)	(0.015)	(0.020)	(0.033)
Export quantity	0.152^a	0.285^a	0.262^a	0.423^a	0.464^a	0.257^b	0.139^a	0.292^a	0.302^a
	(0.019)	(0.024)	(0.039)	(0.035)	(0.047)	(0.119)	(0.020)	(0.025)	(0.041)
	Extensive margin								
No. of destinations	0.012^a	0.098^a	0.058^a	0.158^a	0.167^a	0.096^b	-0.002	0.089^a	0.049^a
	(0.006)	(0.008)	(0.013)	(0.012)	(0.016)	(0.041)	(0.006)	(0.008)	(0.014)
No. of products	0.039^a	0.143^a	0.103^a	0.222^a	0.242^a	0.175^a	0.023^a	0.141^a	0.104^a
	(0.008)	(0.011)	(0.018)	(0.016)	(0.022)	(0.055)	(0.009)	(0.011)	(0.019)
Participation dummy	0.007^a	0.016^a	0.009^a	0.026^a	0.027^a	0.020^a	0.005^a	0.015^a	0.010^a
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.007)	(0.001)	(0.001)	(0.002)

Note: This table provides the ATT estimates for the five dependent variables. All trade margin measures are in logarithm, except the participation dummy. Propensity scores upon which the matching is made are computed using predictions from the estimation of equation (7). M_{it}, M_{it}^{HS} and M_{it}^{LS} respectively denote the number of foreign-born workers in all, high- and low-skilled occupations in firm i at time t. We match firms using the estimated propensity scores from the same sector-region-year triplet. Robust standard errors are shown in parentheses. ^{a}, ^{b} and ^{c} respectively denote significance at the 1%, 5% and 10% levels.

Table 12: Average treatment effect on treated - Logit estimation for scores

Treatment (D_{it})	(1) $M_{it} > 0$	(2) $M_{it} > M_{it-1}$	(3) $M_{it} > M_{it-1}$ $M_{it-1} > 0$	(4) $M_{it}^{HS} > 0$	(5) $M_{it}^{HS} > M_{it-1}^{HS}$	(6) $M_{it}^{HS} > M_{it-1}^{HS}$ $M_{it-1}^{HS} > 0$	(7) $M_{it}^{LS} > 0$	(8) $M_{it}^{LS} > M_{it-1}^{LS}$	(9) $M_{it}^{LS} > M_{it-1}^{LS}$ $M_{it-1}^{LS} > 0$
Propensity score estimator	Logit								
Matching algorithm	Closest neighbour								
Matching constraint	Sector-region								
Intensive margin									
Export value	0.368^a	0.214^a	0.287^a	0.325^a	0.285^a	0.218^b	0.353^a	0.216^a	0.296^a
	(0.015)	(0.019)	(0.032)	(0.031)	(0.038)	(0.099)	(0.016)	(0.020)	(0.033)
Export quantity	0.408^a	0.229^a	0.349^a	0.282^a	0.224^a	0.012	0.421^a	0.262^a	0.350^a
	(0.020)	(0.024)	(0.040)	(0.038)	(0.048)	(0.120)	(0.020)	(0.025)	(0.041)
Extensive margin									
No. of destinations	0.113^a	0.074^a	0.094^a	0.114^a	0.075^a	0.021	0.106^a	0.076^a	0.089^a
	(0.006)	(0.008)	(0.013)	(0.013)	(0.016)	(0.041)	(0.006)	(0.008)	(0.014)
No. of products	0.176^a	0.106^a	0.148^a	0.162^a	0.120^a	0.046	0.166^a	0.113^a	0.142^a
	(0.009)	(0.011)	(0.018)	(0.017)	(0.022)	(0.056)	(0.009)	(0.011)	(0.019)
Participation dummy	0.022^a	0.014^a	0.019^a	0.012^a	0.013^a	0.007	0.021^a	0.015^a	0.019^a
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.007)	(0.001)	(0.001)	(0.002)

Note: This table provides the ATT estimates for the five dependent variables. All trade margin measures are in logarithm, except the participation dummy. Propensity scores upon which the matching is made are computed using predictions from the estimation of equation (7) using a logit estimator. M_{it}, M_{it}^{HS} and M_{it}^{LS} respectively denote the number of foreign-born workers in all, high- and low-skilled occupations in firm i at time t. We match firms using the estimated propensity scores from the same sector-region. Robust standard errors are shown in parentheses. ^{a}, ^{b} and ^{c} respectively denote significance at the 1%, 5% and 10% levels.

Table 13: Average treatment effect on treated - Scores with noise

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment (D_{it})	$\mathrm{M}_{it} > 0$	$\mathrm{M}_{it} > \mathrm{M}_{it-1}$	$\mathrm{M}_{it} > \mathrm{M}_{it-1}$ $\mathrm{M}_{it-1} > 0$	$\mathrm{M}_{it}^{HS} > 0$	$\mathrm{M}_{it}^{HS} > \mathrm{M}_{it-1}^{HS}$	$\mathrm{M}_{it}^{HS} > \mathrm{M}_{it-1}^{HS}$ $\mathrm{M}_{it-1}^{HS} > 0$	$\mathrm{M}_{it}^{LS} > 0$	$\mathrm{M}_{it}^{LS} > \mathrm{M}_{it-1}^{LS}$	$\mathrm{M}_{it}^{LS} > \mathrm{M}_{it-1}^{LS}$ $\mathrm{M}_{it-1}^{LS} > 0$
Propensity score estimator	LPM								
Matching algorithm	Closest neighbour								
Matching constraint	Sector-region								
	Intensive margin								
Export value	0.350^{a}	0.376^{a}	0.494^{a}	0.962^{a}	0.878^{a}	1.093^{a}	0.300^{a}	0.305^{a}	0.430^{a}
	(0.014)	(0.019)	(0.031)	(0.027)	(0.037)	(0.095)	(0.014)	(0.020)	(0.033)
Export quantity	0.416^{a}	0.406^{a}	0.570^{a}	0.924^{a}	0.869^{a}	0.889^{a}	0.391^{a}	0.371^{a}	0.554^{a}
	(0.018)	(0.024)	(0.039)	(0.034)	(0.047)	(0.116)	(0.018)	(0.025)	(0.041)
	Extensive margin								
No. of destinations	0.107^{a}	0.132^{a}	0.156^{a}	0.346^{a}	0.318^{a}	0.340^{a}	0.084^{a}	0.106^{a}	0.127^{a}
	(0.006)	(0.008)	(0.013)	(0.011)	(0.016)	(0.040)	(0.006)	(0.008)	(0.013)
No. of products	0.177^{a}	0.199^{a}	0.247^{a}	0.482^{a}	0.445^{a}	0.501^{a}	0.145^{a}	0.170^{a}	0.215^{a}
	(0.008)	(0.010)	(0.017)	(0.015)	(0.021)	(0.053)	(0.008)	(0.011)	(0.018)
Participation dummy	0.031^{a}	0.027^{a}	0.036^{a}	0.081^{a}	0.070^{a}	0.079^{a}	0.027^{a}	0.024^{a}	0.032^{a}
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.007)	(0.001)	(0.001)	(0.002)

Note: This table provides the ATT estimates for the five dependent variables. All trade margin measures are in logarithm, except the participation dummy. Propensity scores upon which the matching is made are computed using predictions from the estimation of equation (7) using a linear probability model. Scores are then multiplied by a random term between zero and unity. M_{it}, M_{it}^{HS} and M_{it}^{LS} respectively denote the number of foreign-born workers in all, high- and low-skilled occupations in firm i at time t. We match firms using the estimated propensity scores from the same sector-region. Robust standard errors are shown in parentheses. ^{a}, ^{b} and ^{c} respectively denote significance at the 1%, 5% and 10% levels.

Table 14: Average treatment effect on treated - 5 neighbour matching algorithm

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment (D_{it})	$\mathrm{M}_{it} > 0$	$\mathrm{M}_{it} > \mathrm{M}_{it-1}$	$\mathrm{M}_{it} > \mathrm{M}_{it-1}$ $\mathrm{M}_{it-1} > 0$	$\mathrm{M}_{it}^{HS} > 0$	$\mathrm{M}_{it}^{HS} > \mathrm{M}_{it-1}^{HS}$	$\mathrm{M}_{it}^{HS} > \mathrm{M}_{it-1}^{HS}$ $\mathrm{M}_{it-1}^{HS} > 0$	$\mathrm{M}_{it}^{LS} > 0$	$\mathrm{M}_{it}^{LS} > \mathrm{M}_{it-1}^{LS}$	$\mathrm{M}_{it}^{LS} > \mathrm{M}_{it-1}^{LS}$ $\mathrm{M}_{it-1}^{LS} > 0$
Propensity score estimator	LPM								
Matching algorithm	5 neighbours								
Matching constraint	Sector-region								
Intensive margin									
Export value	0.118^a	0.245^a	0.152^a	0.496^a	0.433^a	0.284^a	0.086^a	0.220^a	0.142^a
	(0.012)	(0.015)	(0.025)	(0.023)	(0.030)	(0.077)	(0.013)	(0.016)	(0.026)
Export quantity	0.172^a	0.272^a	0.192^a	0.413^a	0.368^a	0.063	0.167^a	0.269^a	0.225^a
	(0.016)	(0.019)	(0.031)	(0.029)	(0.038)	(0.094)	(0.016)	(0.020)	(0.032)
Extensive margin									
No. of destinations	0.019^a	0.094^a	0.036^a	0.163^a	0.145^a	0.045	0.007	0.082^a	0.032^a
	(0.005)	(0.006)	(0.010)	(0.010)	(0.013)	(0.032)	(0.005)	(0.006)	(0.011)
No. of products	0.049^a	0.139^a	0.069^a	0.226^a	0.207^a	0.091^b	0.033^a	0.127^a	0.067^a
	(0.007)	(0.008)	(0.014)	(0.013)	(0.017)	(0.044)	(0.007)	(0.009)	(0.015)
Participation dummy	0.006^a	0.015^a	0.006^a	0.022^a	0.022^a	0.004	0.005^a	0.014^a	0.007^a
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.006)	(0.001)	(0.001)	(0.001)

Note: This table provides the ATT estimates for the five dependent variables. All trade margin measures are in logarithm, except the participation dummy. Propensity scores upon which the matching is made are computed using predictions from the estimation of equation (7). M_{it}, M_{it}^{HS} and M_{it}^{LS} respectively denote the number of foreign-born workers in all, high- and low-skilled occupations in firm i at time t. We match firms using the estimated propensity scores from the same sector-region. We use a 5-neighbour matching procedure. Robust standard errors are shown in parentheses. ^{a}, ^{b} and ^{c} respectively denote significance at the 1%, 5% and 10% levels.

Table 15: Average treatment effect on treated - Closest neighbour and no replacement

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment (D_{it})	$\mathrm{M}_{it} > 0$	$\mathrm{M}_{it} > \mathrm{M}_{it-1}$	$\mathrm{M}_{it} > \mathrm{M}_{it-1}$ $\mathrm{M}_{it-1} > 0$	$\mathrm{M}_{it}^{HS} > 0$	$\mathrm{M}_{it}^{HS} > \mathrm{M}_{it-1}^{HS}$	$\mathrm{M}_{it}^{HS} > \mathrm{M}_{it-1}^{HS}$ $\mathrm{M}_{it-1}^{HS} > 0$	$\mathrm{M}_{it}^{LS} > 0$	$\mathrm{M}_{it}^{LS} > \mathrm{M}_{it-1}^{LS}$	$\mathrm{M}_{it}^{LS} > \mathrm{M}_{it-1}^{LS}$ $\mathrm{M}_{it-1}^{LS} > 0$
Propensity score estimator	LPM								
Matching algorithm	Closest neighbour and no replacement								
Matching constraint	Sector-region								
	Intensive margin								
Export value	0.353^a	0.259^a	0.126^a	0.620^a	0.404^a	0.264^a	0.299^a	0.241^a	0.154^a
	(0.011)	(0.018)	(0.031)	(0.026)	(0.037)	(0.097)	(0.012)	(0.018)	(0.032)
Export quantity	0.429^a	0.274^a	0.157^a	0.543^a	0.349^a	0.120	0.405^a	0.288^a	0.214^a
	(0.015)	(0.023)	(0.038)	(0.033)	(0.047)	(0.118)	(0.015)	(0.023)	(0.040)
	Extensive margin								
No. of destinations	0.103^a	0.098^a	0.028^b	0.217^a	0.144^a	0.065	0.081^a	0.092^a	0.032^b
	(0.005)	(0.007)	(0.013)	(0.011)	(0.016)	(0.041)	(0.005)	(0.008)	(0.013)
No. of products	0.168^a	0.147^a	0.056^a	0.296^a	0.200^a	0.110^b	0.141^a	0.137^a	0.072^a
	(0.006)	(0.010)	(0.017)	(0.015)	(0.021)	(0.055)	(0.008)	(0.010)	(0.018)
Participation dummy	0.017^a	0.014^a	0.005^a	0.033^a	0.023^a	0.004	0.014^a	0.014^a	0.006^a
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.007)	(0.001)	(0.001)	(0.002)

Note: This table provides the ATT estimates for the five dependent variables. All trade margin measures are in logarithm, except the participation dummy. Propensity scores upon which the matching is made are computed using predictions from the estimation of equation (7). M_{it}, M_{it}^{HS} and M_{it}^{LS} respectively denote the number of foreign-born workers in all, high- and low-skilled occupations in firm i at time t. We match firms using the estimated propensity scores from the same sector-region. We use the closest neighbour matching algorithm with no replacement. Robust standard errors are shown in parentheses. ^{a}, ^{b} and ^{c} respectively denote significance at the 1%, 5% and 10% levels.

Table 16: Average treatment effect on treated - Controlling for firm-destination-year shocks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treatment (D_{it})	$\mathrm{M}_{it} > 0$	$\mathrm{M}_{it} > \mathrm{M}_{it-1}$	$\mathrm{M}_{it} > \mathrm{M}_{it-1}$ $\mathrm{M}_{it-1} > 0$	$\mathrm{M}_{it}^{HS} > 0$	$\mathrm{M}_{it}^{HS} > \mathrm{M}_{it-1}^{HS}$	$\mathrm{M}_{it}^{HS} > \mathrm{M}_{it-1}^{HS}$ $\mathrm{M}_{it-1}^{HS} > 0$	$\mathrm{M}_{it}^{LS} > 0$	$\mathrm{M}_{it}^{LS} > \mathrm{M}_{it-1}^{LS}$	$\mathrm{M}_{it}^{LS} > \mathrm{M}_{it-1}^{LS}$ $\mathrm{M}_{it-1}^{LS} > 0$
	LPM score estimator, Closest neighbour algorithm, Sector-region-import growth quartile match								
$\hat{\gamma}_{it}$	0.072^a	0.081^a	0.079^a	0.128^a	0.110^a	0.109^c	0.055^a	0.073^a	0.047^c
	(0.013)	(0.015)	(0.024)	(0.020)	(0.025)	(0.060)	(0.014)	(0.016)	(0.026)
	LPM score estimator, Closest neighbour algorithm, Sector-region-export growth quartile match								
$\hat{\gamma}_{it}$	0.089^a	0.113^a	0.107^a	0.202^a	0.193^a	0.192^a	0.072^a	0.104^a	0.093^a
	(0.011)	(0.013)	(0.022)	(0.018)	(0.024)	(0.057)	(0.012)	(0.014)	(0.024)
	LPM score estimator, Closest neighbour algorithm, Sector-region-year match								
$\hat{\gamma}_{it}$	0.076^a	0.136^a	0.155^a	0.215^a	0.227^a	0.310^a	0.060^a	0.125^a	0.152^a
	(0.011)	(0.013)	(0.022)	(0.017)	(0.023)	(0.057)	(0.011)	(0.014)	(0.023)
	Logit score estimator, Closest neighbour algorithm, Sector-region match								
$\hat{\gamma}_{it}$	0.186^a	0.113^a	0.146^a	0.150^a	0.135^a	0.153^a	0.177^a	0.112^a	0.141^a
	(0.012)	(0.013)	(0.022)	(0.019)	(0.029)	(0.058)	(0.012)	(0.014)	(0.023)
	LPM score estimator with noise, Closest neighbour algorithm, Sector-region match								
$\hat{\gamma}_{it}$	0.181^a	0.175^a	0.260^a	0.364^a	0.348^a	0.509^a	0.148^a	0.160^a	0.204^a
	(0.010)	(0.013)	(0.021)	(0.018)	(0.023)	(0.056)	(0.011)	(0.014)	(0.023)
	LPM score estimator, 5 neighbour algorithm, Sector-region match								
$\hat{\gamma}_{it}$	0.090^a	0.131^a	0.130^a	0.213^a	0.208^a	0.205^a	0.074^a	0.119^a	0.114^a
	(0.009)	(0.011)	(0.017)	(0.014)	(0.018)	(0.045)	(0.009)	(0.011)	(0.018)
	LPM score estimator, Closest neighbour & no replacement algorithm, Sector-region match								
$\hat{\gamma}_{it}$	0.177^a	0.129^a	0.125^a	0.261^a	0.177^a	0.179^a	0.157^a	0.114^a	0.112^a
	(0.008)	(0.013)	(0.021)	(0.015)	(0.023)	(0.056)	(0.008)	(0.013)	(0.022)

Note: This table provides the ATT estimates for the predicted firm-year fixed effect ($\hat{\gamma}_{it}$) from equation (16). Propensity scores upon which the matching is made are computed using predictions from the estimation of equation (7). M_{it}, M_{it}^{HS} and M_{it}^{LS} respectively denote the number of foreign-born workers in all, high- and low-skilled occupations in firm i at time t. Robust standard errors are shown in parentheses. ^{a}, ^{b} and ^{c} respectively denote significance at the 1%, 5% and 10% levels.

Table 17: Matching quality - Beyond the destination-specific effect of immigrant workers

	$\hat{\gamma_{it}}$			Export concentration		
Treatment (D_{it})	$M_{it} > 0$					
Propensity score estimator	LPM			LPM		
Matching algorithm	Closest neighbour			Closest neighbour		
Matching constraint	Sector-region			Sector-region		
	Treated	Control	% bias	Treated	Control	% bias
(log) Mean age of workers	3.619	3.625	-2.9	3.615	3.621	-2.7
(log) No. of CS1	1.315	1.272	13.5	1.293	1.266	8.7
Herf. CS1	0.629	0.639	-4.5	0.645	0.648	-1.6
(log) Firm age	2.824	2.839	-2.1	2.793	2.804	-1.7
(log) Employment	3.209	3.202	0.5	2.994	2.974	1.4
(log) Assets	8.290	8.341	-3.2	7.922	7.967	-2.9
(log) Own resources	0.094	0.094	-1.5	0.094	0.094	-2.0

Note: This table provides the observed means of firm characteristics (C_{it}) for the treated and the control groups after score matching and computation of the ATT on the predicted firm-year fixed effect from equation (16) ($\hat{\gamma_{it}}$) and the Herfindahl index of concentration of exports for a given firm-year (Table 6). All variables are lagged ($t-1$). We compare the two means using a relative bias measures, relating the quality of the matching procedure. *% bias* denotes the normalized relative bias between the two means (Austin, 2009).

Table 18: Destination-specific effect and immigrant workers – OLS results

	$\hat{\gamma_{it}}$			Export concentration		
	(1)	(2)	(3)	(4)	(5)	(6)
D_{it}	0.060^a			-0.009^a		
	(0.005)			(0.001)		
D_{it}^{HS}		0.058^a			-0.008^a	
		(0.008)			(0.001)	
D_{it}^{LS}			0.059^a			-0.010^a
			(0.005)			(0.001)
Firm FE	yes	yes	yes	yes	yes	yes
Sector-region FE	yes	yes	yes	yes	yes	yes
Sector-year FE	yes	yes	yes	yes	yes	yes
Obs.	392,540	392,540	392,540	675,572	675,572	675,572
R^2	0.814	0.815	0.815	0.743	0.743	0.743

Note: This table provides OLS estimates for the predicted firm-year fixed effect ($\hat{\gamma_{it}}$) from equation (16) and for the Herfindahl index of concentration of exports for a given firm-year. D_{it} , D_{it}^{HS} and D_{it}^{LS} respectively denote a dummy variable equal to 1 if the firm employs a positive number of immigrant workers in all, low- and high-skilled occupations. Standard errors, clustered at the sector-year level, are shown in parentheses. a, b and c respectively denote significance at the 1%, 5% and 10% levels.

Table 19: Average treatment effect on treated - Corollary

Treatment (D_{it})	(1) $M_{it} > 0$	(2) $M_{it} > M_{it-1}$	(3) $M_{it} > M_{it-1}$ $M_{it-1} > 0$	(4) $M^{HS}_{it} > 0$	(5) $M^{HS}_{it} > M^{HS}_{it-1}$	(6) $M^{HS}_{it} > M^{HS}_{it-1}$ $M^{HS}_{it-1} > 0$	(7) $M^{LS}_{it} > 0$	(8) $M^{LS}_{it} > M^{LS}_{it-1}$	(9) $M^{LS}_{it} > M^{LS}_{it-1}$ $M^{LS}_{it-1} > 0$
	LPM score estimator, Closest neighbour algorithm, Sector-region-import growth quartile match								
Export concentration	-0.005^b	-0.009^a	-0.002	-0.019^a	-0.015^a	-0.001	-0.003	-0.009^a	-0.000
	(0.002)	(0.003)	(0.004)	(0.004)	(0.005)	(0.011)	(0.002)	(0.003)	(0.005)
	LPM score estimator, Closest neighbour algorithm, Sector-region-export growth quartile match								
Export concentration	-0.001	-0.014^a	0.001	-0.025^a	-0.025^a	-0.012	-0.000	-0.011^a	0.000
	(0.002)	(0.002)	(0.004)	(0.003)	(0.004)	(0.011)	(0.002)	(0.003)	(0.004)
	LPM score estimator, Closest neighbour algorithm, Sector-region-year match								
Export concentration	-0.001	-0.020^a	-0.009^b	-0.031^a	-0.034^a	-0.015	0.002	-0.018^a	-0.006
	(0.002)	(0.002)	(0.004)	(0.003)	(0.004)	(0.010)	(0.002)	(0.002)	(0.004)
	Logit score estimator, Closest neighbour algorithm, Sector-region match								
Export concentration	-0.024^a	-0.017^a	-0.015	-0.022^a	-0.014^a	0.005	-0.022^a	-0.015^a	-0.017^a
	(0.002)	(0.002)	(0.004)	(0.003)	(0.004)	(0.010)	(0.002)	(0.002)	(0.004)
	LPM score estimator with noise, Closest neighbour algorithm, Sector-region match								
Export concentration	-0.020^a	-0.027^a	-0.027^a	-0.070^a	-0.066^a	-0.061^a	-0.016^a	-0.022^a	-0.024^a
	(0.002)	(0.002)	(0.004)	(0.003)	(0.004)	(0.010)	(0.002)	(0.002)	(0.004)
	LPM score estimator, 5 neighbour algorithm, Sector-region match								
Export concentration	-0.002	-0.018^a	-0.003	-0.031^a	-0.030^a	-0.003	0.000	-0.015^a	-0.003
	(0.001)	(0.002)	(0.003)	(0.003)	(0.003)	(0.008)	(0.001)	(0.002)	(0.003)
	LPM score estimator, Closest neighbour & no replacement algorithm, Sector-region match								
Export concentration	-0.022^a	-0.019^a	-0.000	-0.046^a	-0.033^a	-0.009	-0.017^a	-0.019^a	-0.003
	(0.001)	(0.002)	(0.004)	(0.003)	(0.004)	(0.010)	(0.001)	(0.002)	(0.004)

Note: This table provides the ATT estimates for the Herfindahl index of concentration of exports for a given firm-year. Propensity scores upon which the matching is made are computed using predictions from the estimation of equation (7). M_{it}, M^{HS}_{it} and M^{LS}_{it} respectively denote the number of foreign-born workers in all, high- and low-skilled occupations in firm i at time t. Robust standard errors are shown in parentheses. ^{a}, ^{b} and ^{c} respectively denote significance at the 1%, 5% and 10% levels.

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