# Does Exporting Improve Matching? Evidence from French Employer-Employee Data

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June 2014

**Abstract**

This paper documents the difference in the sorting patterns of workers between exporters and non-exporters in a French matched employer-employee dataset. We extract the type of each worker from a wage regression and construct measures of the average type and type dispersion at the firm level. We find that exporting firms tolerate a lower dispersion in the pool of workers they hire. The matching between exporting firms and workers is even tighter in sectors characterized by better exporting opportunities as measured by foreign demand or tariffs. We also confirm the conjecture in the literature that exporters pay higher wages because, among other factors, they employ better workers. The findings are consistent with a model of matching between heterogeneous workers and firms where variation in the worker type at the firm level exists in equilibrium only because of the presence of search costs. When firms gain access to the foreign market their revenue potential increases. When stakes are high, matching with the right worker becomes particularly important because deviations from the ideal match quickly reduce the value of the relationship. Hence exporting firms select sets of workers that are less dispersed relative to the average.

We would like to thank Keith Head, Francesco Trebbi and seminar participants at the University of British Columbia and Università Bocconi.

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# 1 Introduction

The pattern of sorting of workers across firms has fundamental implications for the efficiency of the economy as well as for the inequality of wages in the labor force. The first implication has been a concern of the literature on assignment starting from Shapley & Shubik (1971) and Becker (1973). From those contributions we know that when firms and workers are complementary in production then the allocation of the right worker to the right job maximizes output. The second implication has received attention more recently for example by Card et al. (2013), who show that sorting of good workers to good firms can explain as much as 35% of the recent increase in wage inequality in West Germany. The logic by which highly skilled workers are paid more not only because of their innate higher productivity, but also because they work with highly productive firms and co-workers, is common to the contribution by Kremer & Maskin (1996) as well.

In this paper we start from the premise that the optimal allocation of workers cannot be reached because of the presence of search costs, and therefore firms accept some degree of mismatch in equilibrium because the cost of search exceeds the benefit from a more suited partner. We then explore whether the matching of firms and workers is affected by access of the former to the export market. But how can market integration affect how firms and workers are matched? When firms gain access to the foreign market their revenue potential increases. When stakes are high, matching with the right worker becomes particularly important because deviations from the ideal match quickly reduce the value of the relationship.

Using matched employer-employee data from France, we show that exporters select pools of workers characterized by higher average type and lower type dispersion than non-exporting firms. While the first effect is predicted by other models (Helpman et al.,2010 and Sampson,2012) we believe we offer a novel way of testing this prediction, which disentangles pure exporter wage

premia (deriving from profit-sharing with workers as in Amiti & Cameron ,2012) from the selection of better workers by exporting firms. The second effect, i.e. the influence of exporting on worker type dispersion, is unexplored in the literature and is quantitatively as strong as the effect of exporting on worker average type. We explore further the effect of exporting by building measures of the exporting opportunities in different sectors using tariffs and aggregate imports from the rest of the world of the various countries that France exports to. Whether we build these measures at the firm or at the sector level (using previous period export shares), we find that when exporters face lower tariffs or larger demand for imports in a foreign market, the dispersion of types in their pool of workers declines further. We believe this result is harder to reconcile with a view that the exporting and tightening of the matching are both driven by a common excluded factor.

To study the impact of exporting on matching we employ the model proposed by Eeckhout & Kircher (2011), where we show that exporting is identical to an increase in the firm's type. Heterogeneous workers and firms face a dynamic problem where in the first period they meet at random and decide whether to accept the match or not. If they do not accept the match they pay a search cost and proceed to the second period where perfect assortative matching prevails. The second period, rather than an infinite horizon, approximates the long run outside option for both worker and firm. The presence of search costs creates an acceptance set, rather than a unique assignment outcome that prevails in the frictionless model. As shown by Eeckhout & Kircher (2011), the boundaries of such acceptance set are increasing in firm type, confirming the pattern of positive assortative matching in a model with frictions. We focus on a different dimension and we take the width of the acceptance set as a measure of the variability in worker type tolerated by the firm.

On the one hand, because of complementarity a worker with type below the firm's ideal creates

a reduction in output that is larger when the firm is very productive. On the other hand a worker type that is above the average type requires an increasing compensation due to her outside option. Such compensation rises much faster at firms that are more productive because they employ on average more productive types. The result is that firms that are more productive tolerate less relative dispersion from their ideal worker type.

This paper contributes to the growing literature on international trade with heterogeneous labor and firms, which is surveyed in a recent chapter by Davidson & Sly (2012). More specifically it belongs to a strand of research that investigates the effect of openness on the process of matching between firms and workers, which is at the core contribution by Sampson (2012), who studies its consequences for wage inequality.[1]

The most closely related work is a recent paper by Davidson et al. (2012), which shows, using Swedish data, that export-oriented sectors display a higher correlation between firm and worker types, estimated as firms' and workers' fixed effects in a wage regression as in Abowd et al. (1999)(henceforth AKM).

Our approach shifts the focus on the firm-level decision rather than looking at the aggregate strength of matching and therefore relies on a different type of variation to detect different matching behavior by firms that are differentially exposed to international trade. In particular, it exploits within-sector variation between exporting and non-exporting firms, therefore isolating and controlling for other sector-level characteristics of the labor market that may affect the sorting of workers across firms.

Moreover, because Eeckhout & Kircher (2011) prove that firms fixed effect deriving from a wage regression a la AKM might be negatively or not correlated with the true firm type, we are careful to

[1] Our paper is also related to the large literature on the impact of trade on inequality, which includes, among many others, Feenstra & Hanson (1999), Costinot & Vogel (2010), Bustos (2012), Amiti & Cameron (2012) and Verhoogen (2008).

avoid using those fixed effects as a proxy for the firm's type. We use instead variables constructed from firm-level data, such as sales, value added and total employment.

From a theoretical standpoint our approach differs from Davidson et al. (2008) in that we have a different focus. We are interested in deriving predictions at the firm level, rather than at the aggregate level and therefore we allow for a rich heterogeneity on both the worker and the firm side. Davidson et al. (2008) simplify those dimensions in order to obtain clean aggregate results. In particular they have high and low types of workers and high and low technology. Globalization can take the economy from an equilibrium in which high-tech firms employ high and low-tech firms employ both high and low type workers to an equilibrium where there is perfect assortative matching. The firm-level predictions in their set-up between exporters and non-exporters are stylized in that there is no predicted variation in the type of workers hired by different types of firms under trade.

The relationship of this paper to the theoretical framework in Helpman et al. (2010) and Helpman et al. (2013) deserves a more detailed analysis, since both models describe the matching of heterogeneous firms to heterogeneous workers in the presence of search frictions. The main conceptual difference between the two theoretical approaches is the nature of workers heterogeneity. In Helpman et al. (2010) workers are not ex-ante different, but they have a productivity draw that is firm specific. Therefore there is no sense in which an ex-ante a high-type worker is more likely to match with a high-type firm, since a firm simply select the workers that have better productivity draws relative to *that* firm only. In general our estimation procedure, which presumes the existence of a fixed worker type is incompatible with their view of ex-ante identical workers. Let us for a moment set aside this difference and investigate the predictions of their model in terms of the dispersion of worker types within firms. Under the assumption of a Pareto distribution,

exporters (and more productive firms in general) choose a higher cutoff for hiring workers. This results in a distribution of workers within firm that has higher standard deviation, higher mean and a constant coefficient of variation (the ratio of standard deviation to mean). Therefore we need an alternative theoretical framework to investigate the impact of exporting on matching of permanently heterogeneneous workers and firms that also face the possibility of exporting.

The remainder of the paper is divided in two sections. Section 2 introduces the theoretical framework and derives the main result on the dispersion of worker types at the firm level. Section 3 presents the estimation of worker types and presents empirical results linking export status and dispersion of worker type in the firm.

## 2 Theoretical framework

The role of the theoretical framework is to understand why exporting firms may match with a different pool of workers from non-exporters. In particular, we are interested in two characteristics of the pool of workers hired by exporters: the average worker type and the variation in worker type at the firm level.

The setup is borrowed from Eeckhout & Kircher (2011), a dynamic model where heterogeneous firms and heterogeneous workers match in the presence of search frictions. There is a unit mass of workers and a unit mass of firms. A worker's type $\theta$ is distributed according to a smooth density $g(\theta)$ on the interval $[0, 1]$, while a firm's type $\psi$ is distributed according to smooth density $h(\psi)$ on the interval $[0, 1]$.

Output is produced by a firm that employs one worker, according to the production function $f(\theta, \psi) = (\theta\psi)^{\sigma}$ where $\sigma > 0$. [2] We embed the matching problem in a monopolistic competition

[2] Here we can think of a firm with $n$ workers as solving the same problem $n$ times where the matching with one worker does not affect matching with the other. Nevertheless it is possible to introduce more than one worker in the production function, and therefore interaction between matching with different workers, without altering the

model à la Krugman (1979). Each firm produces a differentiated variety of product. Demand for an individual variety is isoelastic with elasticity $\eta > 1$. Therefore firms selling their output in the domestic market obtain total revenues:

$$R_d(\theta, \psi) = (\theta\psi)^{\frac{\sigma(\eta-1)}{\eta}} E^{\frac{1}{\eta}}$$

where $E$ is domestic total real expenditures. Firm revenues are increasing in the type of the firm and the worker and feature complementarity between the two types, i.e. $f_{\theta\psi} > 0$. Complementarity is key for whether there is positive assortative matching in equilibrium between firms and workers.

Under these assumptions, in the absence of frictions, we would observe perfect positive assortative matching. Under that scenario every type of firms would be matched with a unique type of worker. In particular, a more productive firm would be matched with a more productive worker, but there would be no variation within the set of workers matched with firms of a given type $\psi$, as in Sampson (2012).

We are interested in analyzing the variation between workers employed by the same type of firm. We therefore introduce frictions in the spirit of Atakan (2006), although we follow the timing simplification prosposed by Eeckhout & Kircher (2011). There are two periods. In the first period workers and firms meet at random, they perfectly observe one another's type and decide whether to produce. If they do not produce they pay a cost $c$ to search again in the second period. In the second period matching happens in a frictionless and competitive setting, therefore perfect assortative matching is the equilibrium outcome as in Becker (1973). Before describing how the equilibrium matching is determined we describe how we interpret the exporting decision in this simple set-up.

qualitative results of the model.

We introduce exporting in the simplest possible way, yet one that has similar features to the rest of the literature. There are different options when introducing a firm-level exporting decision. The original contribution by Melitz (2003) simply introduces a fixed cost of exporting common to all firms. This modelling choice implies that we should never observe two firms of the same productivity, but different export status. The stark prediction that all exporters should be more productive than non-exporters is clearly not supported by the data, as argued for example by-Bernard et al. (2003) and Helpman et al. (2013). In both US and Brazilian data the distribution of productivity of exporters has a higher mean, but also displays a substantial overlap with the productivity distribution of non-exporters, a feature that is clearly shared by our French sample as shown in Figure A1.

Because, similarly to Helpman et al. (2013), in our exercise we focus on the effect of exporting separately from that of firm productivity, we adopt a similar strategy of allowing different firms to have different costs of exporting. This may reflect various idiosyncratic factors such as better knowledge of the export market that makes setting up an export operation less costly. Because our interest in this paper is exclusively in comparing exporters and non-exporters and not in the endogenous sorting into exporting or the estimation of the fixed cost of exporting, we make one further simplifying assumption. We assume that some firms draw a prohibitively high fixed cost of exporting, while the rest of the firms draw a negligible fixed cost. All firms that export face an iceberg transport cost $\tau > 1$. This is the simplest way of introducing heterogeneous exporting behavior among firms of identical type.

When a firm exports, its revenues increase even if the firm is not allowed to adjust its workforce. The firm sells its output in a market where the first unit sold of its differentiated variety is valued much more by foreign consumers than the last unit sold in the home market was valued by domestic

consumers. The firm allocates output produced between the two markets so that marginal revenues are equalized in the two markets. This implies that, similarly to Helpman et al. (2010), total revenues of a firm $\psi$ that exports can be written as follows:

$$R_x(\theta, \psi) = (\theta\psi)^{\frac{\sigma(\eta-1)}{\eta}} \left(E + E^* \tau^{1-\eta}\right)^{\frac{1}{\eta}},$$

where $E^*$ is foreign real expenditure.

It is straightforward to verify that, for given $\theta$ and $\psi$, revenues of an exporting firm are larger than those of a non-exporting firm. It is useful to rewrite revenues of an exporting firm and a non-exporting firm with gven productivity $\psi$ as follows:

$$R_d(\theta, \psi) = (A_d \theta\psi)^{\frac{\sigma(\eta-1)}{\eta}}, \tag{1}$$

$$R_x(\theta, \psi) = (A_x \theta\psi)^{\frac{\sigma(\eta-1)}{\eta}} \tag{2}$$

where $A_d = E^{\frac{1}{\sigma(\eta-1)}}$ and $A_x = \left(E + E^* \tau^{1-\eta}\right)^{\frac{1}{\sigma(\eta-1)}}$ and $A^* > A$. We therefore establish the following property.

**Remark 1** *Exporting is isomorphic to an increase in productivity for a firm of initial productivity $\psi$.*

Based on Remark 1 we are going to analyze the effect on matching of export status by characterizing the matching behavior of more productive versus less productive firms.

Until now we have not discussed the distribution of worker types and, more importantly, of firm types. In principle we could start with a specific distribution of firm types $h(\psi)$, introduce export opportunities and derive a distribution of types based on *adjusted* firm type $A_i\psi$ where $i = d, x$. For the sake of tractability we instead make an assumption directly regarding the distribution

of *adjusted* firm types and assume that such distribution is uniform. We define *adjusted* types as $\varphi$. We assume that the distribution of worker types $g(\theta)$ is also uniform as in Eeckhout & Kircher (2011). In the Appendix we start from a uniform distribution for both types and introduce exporting opportunities for a share of the firms. Such exercise is not as clean, but delivers the same implications regarding the matching behavior of exporters.

## 2.1 Matching problem

We now solve the matching problem and derive predictions regarding the matching behavior of exporters versus non-exporting firms. We start by characterizing second period wages, profits and assignment and then analyze period one firms' and workers' decisions. Once again, the problem is analysed in terms of *adjusted* firm type $\varphi$ and worker type $\theta$. We rewrite the revenue function as $R(\theta, \varphi) = (\theta\varphi)^{\alpha}$ where $\alpha = \frac{\sigma(\eta-1)}{\eta}$.

### 2.1.1 Second period: frictionless market

In the second period assignment is positive assortative. The matching function, $\mu(\theta) = \varphi$, which assigns firm $\varphi$ to worker $\theta$ is therefore $\mu(\theta) = \theta$. In a competitive equilibrium the wage function $w(\theta)$ must be such that the marginal revenues for a firm from hiring a better worker is equal to the marginal increase in the wage paid. The equilibrium wage is therefore given by:

$$w^*(\theta) = \int_0^{\theta} \frac{dR(t, \mu(t))}{dt} dt = \frac{1}{2}\theta^{2\alpha} \tag{3}$$

By symmetry equilibium profits in the second period take the same form:

$$\pi^*(\varphi) = \frac{1}{2}\varphi^{2\alpha} \tag{4}$$

### 2.1.2 Acceptance sets

We now determine the matching behavior of firms and workers in the first period. When a worker $\theta$ and a firm $\varphi$ meet they produce $R(\theta, \varphi)$. The outside option for the worker is $w^*(\theta) - c$ while the outside option for the firm is $\pi^*(\varphi) - c$. Regardless of how surplus is split, the worker and the firm will accept to match if the surplus from the relationship is positive, i.e. if the following *surplus condition* holds:

$$(\theta\varphi)^\alpha - \frac{1}{2}\varphi^{2\alpha} - \frac{1}{2}\theta^{2\alpha} + 2c \geq 0 \tag{5}$$

The surplus condition (5) defines the acceptance set, i.e. the set of pairs $(\theta, \varphi)$ where a match is mutually acceptable. The set of workers that match with firm $\varphi$ are denoted by $A(\varphi)$. The boundaries of set $A(\varphi)$ are shown by Eeckhout & Kircher (2011) to be monotonically increasing in $\varphi$, which proves that positive assortative matching holds in the presence of constant search costs.[3] Let us define $u(\varphi)$ and $l(\varphi)$, respectively, the highest and the lowest worker type that matches with firm type $\varphi$. Figure 1 illustrates the acceptance set for $\alpha = 1$ and $c = 0.01$.

We now investigate whether exporting (or more productive) firms tolerate higher or lower variation in the set of workers they match with. We adopt the *matching range* of firm type $\varphi$, $d(\varphi)$, as a measure of the dispersion of workers types tolerated by the firm. The matching range $d(\varphi)$ is defined as the difference between $u(\varphi)$ and $l(\varphi)$. At this point it is important to discuss whether the absolute measure $d(\varphi)$ is an appropriate measure by which we can compare dispersion of worker types within firms that exhibit differences also in the average type of worker hired. Let us take for example the parameterization in figure 1 and consider two firms. Firm $\varphi_H$ hires on average very high worker types and firm $\varphi_L$ hires on average very low worker types. Figure 1 implies that we should observe the same $d(\varphi)$ for both firms, but we would probably not conclude that the

[3] Positive assortative matching requires stronger restrictions on the production function if search costs are due to output loss as in Shimer & Smith (2000).

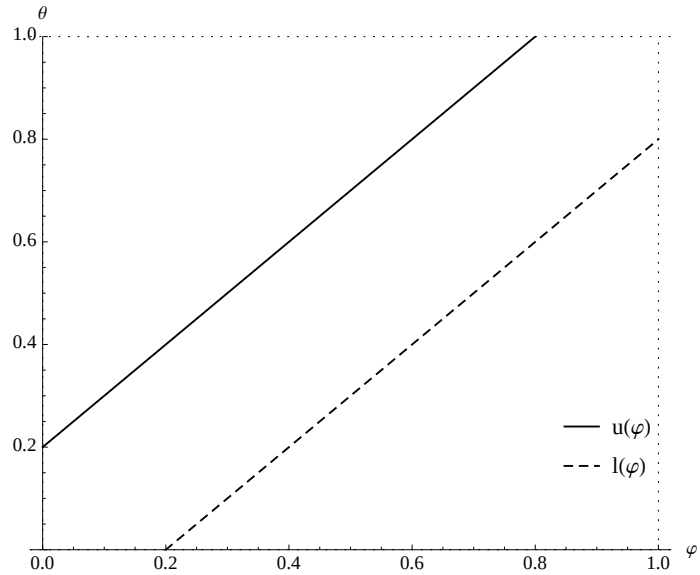


Figure 1: Acceptance set $\alpha = 1$, $c = 0.01$

two firms tolerate the same degree of worker variation. This is because in relative terms firm $\varphi_H$ tolerates less variation relative to the average worker hired than firm $\varphi_L$. Hence we argue that the correct way to analyze the matching range is to adopt scale-free dispersion measures and we propose two alternatives:

(i) a *normalized matching range* $d_1(\varphi)$ where we divide the matching range by the average worker type hired by firm $\varphi$, i.e. $a(\varphi)$. Define $d_1(\varphi) = u_1(\varphi) - l_1(\varphi)$ where $u_1(\varphi) = \frac{u(\varphi)}{a(\varphi)}$ and $l_1(\varphi) = \frac{l(\varphi)}{a(\varphi)}$

(ii) a *logarithmic matching range* $d_2(\ln\varphi)$ i.e. a measure defined on a logarithmic scale so that dispersion is defined in relative deviations. Define $d_2(\ln\varphi) = u_2(\varphi) - l_2(\varphi)$ where $u_2(\varphi) = \ln u(\varphi)$ and $l_2(\varphi) = \ln l(\varphi)$.

The following proposition establishes the main result regarding variability of worker types at more productive firms and exporters.

**Proposition 1** *Dispersion of worker types working at firm $\varphi$, as measured by*

*(i) normalized matching range* $d_1(\varphi)$ *and*

*(ii) logarithmic matching range* $d_2(\ln\varphi)$

*is decreasing in firm type (and is therefore lower for exporting firms relative to non-exporting firms of identical productivity).*

**Proof.** *(i)* It is immediate to show that $u_1(\varphi) = \frac{\left(\varphi^{\alpha}+2\sqrt{c}\right)^{\frac{1}{\alpha}}}{\varphi} = \left(1+\frac{2\sqrt{c}}{\varphi^{\alpha}}\right)^{\frac{1}{\alpha}}$ is a decreasing function of $\varphi$. Similarly one can show that $l_1(\varphi)$ is an increasing function of $\varphi$. Therefore the difference between $u_1(\varphi)$ and $l_1(\varphi)$ is decreasing.

*(ii)* In order to prove that $d_2(\ln\varphi)$ we are going to show that $\frac{du_2(\varphi)}{d\ln\varphi} < 1$ and that $\frac{dl_2(\varphi)}{d\ln\varphi} > 1$. Starting from $u(\varphi) = (\varphi^{\alpha}+2\sqrt{c})^{\frac{1}{\alpha}}$ it is immediate to show that $u_2(\varphi) = \frac{1}{\alpha}\ln\left(e^{\alpha\ln\varphi}+2\sqrt{c}\right)$ and that $\frac{du_2(\varphi)}{d\ln\varphi} = \frac{e^{\alpha\ln\varphi}}{e^{\alpha\ln\varphi}+2\sqrt{c}}$ which is always smaller than one. Similar steps imply that $\frac{dl_2(\varphi)}{d\ln\varphi} > 1$. ■

Figure 2 presents the two normalized measures with the same parameterization as figure 1.

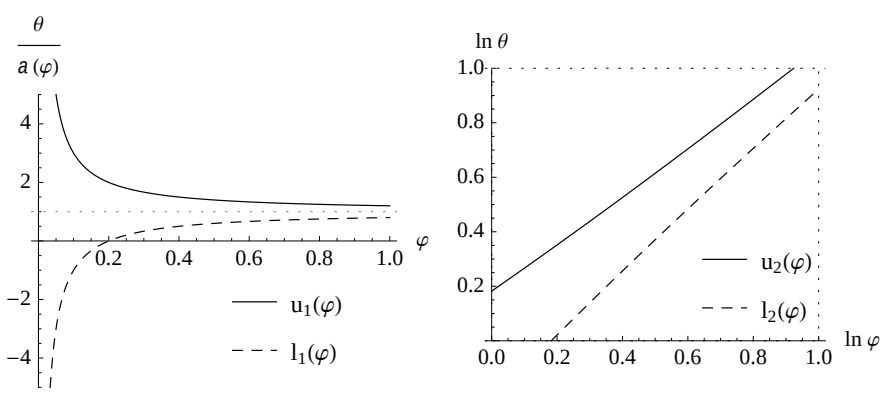


Figure 2: Normalized matching range $\alpha = 1$, $c = 0.01$

The result in proposition 1 is easy to explain once we express the surplus condition (5) in terms of normalized worker types. Let us define $\widehat{\theta} = \frac{\theta}{a(\varphi)} = \frac{\theta}{\varphi}$, the type of a worker, relative to the

average type employed by a firm $\varphi$. Condition (5) can be rewritten as a function of $\widehat{\theta}$ as follows:

$$\underbrace{\left[\widehat{\theta}^{\alpha} - \frac{1}{2}\widehat{\theta}^{2\alpha} - \frac{1}{2}\right]\varphi^{2\alpha}}_{S\left(\widehat{\theta},\varphi\right)} + 2c \geq 0 \tag{6}$$

We analyze the behavior of the function $S\left(\widehat{\theta},\varphi\right)$ and the search costs in figure 3. The function $S\left(\widehat{\theta},\varphi\right)$ is maximized at $\widehat{\theta} = 1$ and drops as one moves away from this perfect PAM allocation. The important feature for our purpose is that $S\left(\widehat{\theta},\varphi\right)$ drops more steeply on either side of $\widehat{\theta} = 1$ when $\varphi$ is higher. This means that the same proportional deviation from the optimal worker produces a larger loss in surplus at larger firms. Higher type firms therefore have a narrower range over which $S\left(\widehat{\theta},\varphi\right) > -2c$ as figure 3 clearly shows.

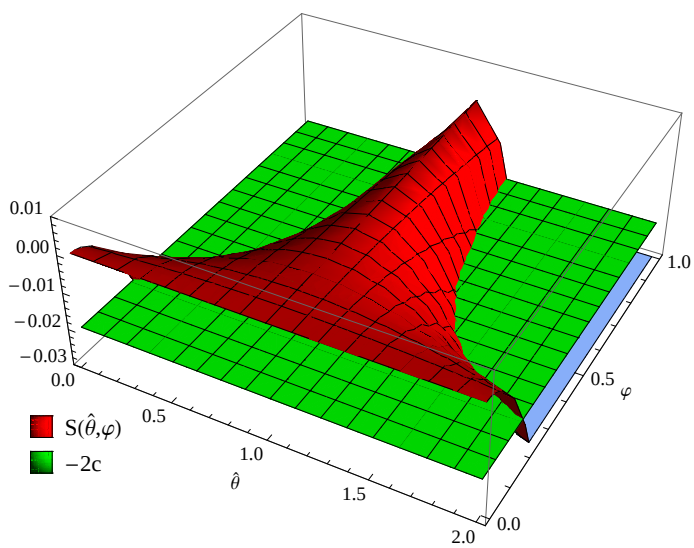


Figure 3: Surplus condition as a function of normalized worker types for $\alpha = 1$, $c = 0.01$

### 2.1.3 One firm with $n$ workers

The model we have analyzed so far entails only one worker. In that context we have said that we can interpret a firm as a collection of hiring decisions that are independent from one another.

One may wonder whether adding more workers to the problem modifies the results. In principle there is a somewhat distinct reason why firms may not want to hire very heterogeneous sets of workers and that is because workers types are complementary to one another. Because of complementarity with the firm type this effect is stronger for more productive firms. As a result this effect will strengthen the logic that we have illustrated in the one-worker setup. Consider for example the case of two workers: $\theta_1$ and $\theta_2$ where the production function is $R(\varphi, \theta_1, \theta_2) = (\varphi\theta_1\theta_2)^\alpha$ Assuming that in case of disagreement the firm cannot produce with only one worker, the surplus condition is very similar to (6) and we can write it in normalized terms analogously to (6):

$$\left[\left(\widehat{\theta}_1\widehat{\theta}_2\right)^\alpha - \frac{1}{3}\widehat{\theta}_1^{3\alpha} - \frac{1}{3}\widehat{\theta}_2^{3\alpha} - \frac{1}{3}\right]\varphi^{3\alpha} + 3c \geq 0, \tag{7}$$

where $\widehat{\theta}_i = \frac{\theta_i}{\varphi}$. It is immediate to verify that the same logic applies in this case. Surplus declines faster for more productive firms as they consider worker types that are further away from their ideal. Hence a higher $\varphi$ firm will accept a narrower set of workers than a lower $\varphi$ firm.

In the next section we introduce data and methodology aimed at verifying the empirical content of the results in proposition 1.

# 3 Empirical analysis

Our empirical analysis proceeds in two steps. First, we estimate worker types employing a methodology pioneered by Abowd et al. (1999) (AKM) and recently enriched by Card et al. (2013). We are careful to separately construct measures of the firm type following a recent analysis of the AKM methodology by Eeckhout & Kircher (2011). In a second step we propose various measures that approximate the matching range of individual firms and show that those measures are systematically different between exporters and non exporters, both in the cross section and when export

markets are subject to shocks that affect the profitability of exporting.

Before describing our empirical strategy in details, we offer a brief overview of the features of the wage-setting institutions in France and of the data employed in this paper.

### 3.1 Institutional Background

The features of French institutional background match what is required to address our research question. Our model assumes that wages are the outcome of a bargaining game between firms and workers. This condition is key to the empirical anaylisis in order for wage outcomes to reflect workers' and firms' characteristics. We argue that the French institutional background provides a good approximation of this feature.

Since 1950, wage-setting institutions in France are organized according to a hierchical principle.Wages are bargained at three different levels: (i) at the national level, a binding minimum wage (called Salaire Minimum Interprofessionnel de Croissance, or SMIC hereafter) is set by the government;[4] (ii) at the industry level, employers' organisations and unions negotiate pay scales; wages are, then, negotiated occupation by occupation; (iii) at the firm level, employers and unions usually negotiate wage increases.

Typically, in 1970s and 1980s collective agreements were negotiated within different sectors between unions and employer associations, then extended by the Ministry of Labour to the entire industry, becoming binding also for workers and firms not part of the original negotiation. At the end of the 1980s, more than 95% of the workforce was covered by those collective agreements. However, different laws have strengthened the decentralization of the wage bargaining process in France over the last thirty years. Three channels have been used to promote firm-level agreements: (i) the obligation for firms to negotiate on wages each year, (ii) more possibilities offered to firms

[4]Until 2010, the SMIC was raised each year in July according to a legal formula based on partial indexation to past inflation and to past wage growth.

to deviate from industry-level agreements (*escape clauses*), and (iii) fiscal incentives.[5] In 1982, the Auroux Law introduced the duty for firms with at least 50 employees and an elected union representative to negotiate wages with unions every year, although not the obligation to reach an agreement. Subsequent legislations concerning the working time reduction (Robiens laws in 1996, the first Aubrys law in 1998, the second Aubrys law in 2000) allowed the application of escape clauses to working hours' arrangements, reinforcing the trend towards decentralization

Since the 1980s, firm-level negotiations acquired progressively more importance. By 2005, 41% of the workers employed in private firms with more than 10 employees were covered by a wage agreement signed that very same year (Naboulet & Carlier (2007)).[6] The number of such agreement grew also significantly, from about 3.000 in 1993 to more than 7.500 in 2006.

### 3.2 Data

The data for our project come from three main sources, the Déclaration Annuelle des Données Sociales (DADS), the Enquete Annuelle d'Entreprises (EAE) and the French Customs Data.[7]

DADS is an administrative database of matched employer-employee information collected by the INSEE (Institut Nationale de la Statistique et des Etudes Economique). The data are based on the mandatory reports, filed by employers, of the gross earnings of each employee in compliance with French payroll taxes. All paying-wages 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 INSEE prepares extracts of the original database for research purposes. We rely on the panel version of DADS, which covers all individuals employed in French

[5] In 2008, reduction of social security contributions paid by the employers became conditional upon wage negotiations occurring within the firm.

[6] In 1992, 40% of the workforce was covered by some firm-level agreement. Source: Abowd et al. (2005); authors' calculation based on data from wage structure survey in 1992.

[7] These data are subject to statistical secrecy and have been acceded at CEPII

enterprises born in the month of October of even-numbered years until 2001 and every year after that.[8] This choice is motivated by the need to follow workers across years and job positions in order to recover their type (see *Estimation of Worker Types*).

Our extract stretches from 1995 to 2007. The initial data set contains around 24 million observations (corresponding to the triplet worker-firm-year) which are identified by worker and firm ID (respectively, *nninouv* and *siren*).

For each observation we have information on the individual's gender, year and place of birth, occupation (both 2-digit CS and 4-digit PCS-ESE classification), job spell,[9] full-time/part-time status, annualized real earnings, total number of hours worked as well as the industry of the employing firm (NAF700, 4-digit industry classification). We restrict our sample to full-time employees in manufacturing (NAF 10-33), reducing the total number of observations to $2,662,411$. Most full-time workers are employed at a single firm during the year. Only 6% has more than one employer in a given year; for those, we selected the enterprise at which the individual worked the largest number of days during the year. Finally, to control for possible outliers, we remove those observations whose log annualized real earnings are more than 5 standard deviation away from the predicted wage, based on a linear model including gender, an ile-de-France dummy and in-firm experience. We obtain a final sample of $2,579,414$.

Following EK, in order to construct appropriate measures of firm types, we enrich the available set of firm-level variables by merging DADS with EAE, a survey-based dataset containing balance-sheet information on French firms in manufacturing over the period 1995-2007. The unit of observation in EAE is a firm-year combination; the firm identifier is the same as the firm ID in DADS (*siren*). EAE samples only medium-large enterprises with at least 20 employees. From

[8] In 2002, the sampling methodology has been extended to include all individuals born in the month of October of every year. Currently, the DADS panel represents 1/12th of the total French workforce.

[9] DADS records both the job start date and the number of days the individual worked in a given firm during the calendar year.

EAE we collect information on sales (domestic and exports), total employment, value added and also on the main sector of the firm (NAF700 4-digit classification).[10] The merge with EAE further reduces the sample availability. We restrict our sample to individuals working for firms whose characteristics are available from EAE. Furthermore, we remove those firms whose number of sampled employees from DADS is larger than the effective employment reported in EAE. This provides us a final sample of $1,673,992$ observations on which we implement the AKM decomposition.

Export-related information on French firms come from the French Customs. The custom data includes export records at firm-, product- and destination-level for the universe of exporters located in France.

Finally, aggregated trade flows and applied tariff levels come from standard sources, respectively COMTRADE and WITS. Aggregated trade flows are used to compute aggregated market shocks as (weighted) import demand by all potential French trade partners, while applied tariff levels are used as a second proxy for foreign market openness - average tariff reduction (across all French trade partners) representing a measure of higher market access for French firms.

### 3.3 Estimation of the worker types: AKM

The AKM methodology aims at decomposing individual workers' wages into a firm component and a worker component and has seen a very large number of applications, e.g. Abowd et al. (2003), Abowd et al. (2005), Abowd et al. (2006) Abowd et al. (2007), Abowd et al. (2008), Abowd et al. (2009), Abowd et al. (2009), Carneiro et al. (2012) Torres et al. (2012).

The basic specification relates a measure of log compensation for worker $i$ employed in firm $j$

[10] We compare the firm's industry classification between EAE and DADS and keep only those observations whose industry information coincides between the two sources.

at time $t$ to workers and firms' effects:

$$\ln w_{it} = x'_{it}\beta + \theta_i + \psi_{J(i,t)} + \varepsilon_{it} \tag{8}$$

where $\theta_i$ is worker $i$'s component and $\psi_{J(i,t)}$ is the firm component. The function $J(i,t) = j$ identifies the firm employing worker $i$ at time $t$. The vector $x_{it}$ includes time-varying worker characteristics, therefore the component $\theta_i$ captures persistent differences in compensation explained by ability and other time-invariant worker characteristics. Although persistent differences in compensation could arise also for reasons other than ability differences (e.g. negotiating skills), our theoretical framework suggests that $\theta_i$ is an appropriate proxy for the individual's unobservable true type. In our model, the person effect from a wage decomposition captures the variation in wages across the firms in her matching set.[11] Workers of higher ability tend to match with more productive firms, obtaining on average higher wages. This behaviour creates a mapping of higher ability into higher person effects. We assume that the error term $\varepsilon_{it}$ is iid across time and workers with mean zero. This assumption requires that employment mobility is exogenous, depending only on observable characteristics, person and firm effects. [12]

We follow AKM for the explicit specification of (8). Our dependent variable is the log of annualized real wages.[13] We include as time-varying controls a quartic in employer-specific experience,[14] time-dummies, a dummy for workers residing in ile-de-France and time-varying gender effects (exactly, the interactions of sex with all the other variables).

[11]The person effect captures also changes in the matching bounds, but this effect is negligible if the tail of firm's distribution is not decaying too fast.

[12]This condition is violated if mobility depends, for example, on match-specific components of wages. In the Appendix we include results estimated under the assumption that the error term $\varepsilon_{it}$ includes a match effect $\eta_{iJ(i,t)}$ and an idiosyndratic term as in Card et al. (2013) and Woodcock (2008). The results are in Table A4 and A5.

[13]Working hours are often not reported. The restriction to full-time workers absorbs possible differences in hours worked across individuals.

[14]DADS contains information on the job starting date at a certain firm - we compute the employer-specific experience as a difference between the current year and the first year of employment at the firm.

The panel version of DADS does not contain information on education. AKM obtain information on the highest degree attained from the permanent demographic sample (Echantillon Démographique Permanent, EDP). However, this information would be available, in our case, only for about 20% of the workers in our sample. Thus, we decided not to include a control for schooling in our decomposition.[15]

As described in Abowd et al. (2002), fixed effects for workers and firms can be separately identified only for sets of firms and workers that are 'connected' by moving workers. In fact, the person effect is common to all individual's job spells; its identification requires observing the individual at different employers. Similarly, a firm effect is common to all employees of the firm; identifying the firm effect requires observations on multiple employees of the firm. Identifying both effects requires mobility of workers across firms.[16] The movement of workers between firms characterizes a *connected* group. A connected group is defined by all workers who ever worked for any firm in the group and all firms whose workforce is included in the group. A second group is *unconnected* to the first if no firm in the first group has ever employed any worker from the second group and no firm in the second has ever employed workers from the first. Within each group, we normalize the mean of the fixed effects to zero, therefore it is not possible to identify 1 individual and 1 firm effects per group.

Due to the normalization, comparing fixed effects between groups has no real meaning. Therefore, when comparing workers and firms, we only employ estimated fixed effects from the largest connected group, which represents 88% of the workers in our final sample.

[15] In addition, most of the effect of schooling would be absorbed by the person effect. AKM mention that schooling does not time-vary over their sample.

[16] Let us consider a simple example of how to implement the AKM methodology. Consider a connected group with 2 firms and N workers and suppose that at least one worker, individual 1, is employed in both firms over the sample period. The observed wage differential for individual 1 is entirely attributed to the difference between firms fixed effects. Normalizing the mean firm effect to zero, it is possible to identify one of the fixed effects. A similar argument applies to the identification of the person effect.

The estimation of the fixed effects is performed using the *Gauss-Seidel* algorithm, proposed by Guimaraes & Portugal (2010). Such algorithm consists in solving the partitioned set of normal equations, associated to (8), given an initial guess on the coefficients. Workers' and firms' fixed effects are recovered as coefficients on the dummy variables identifying the worker and the firm at which he's employed. According to Smyth (1996), the *Gauss-Seidel* algorithm achieves a stable but slow convergence, depending on the correlation between the parameter estimators. This implementation has the advantage of not requiring an explicit calculation of inverse matrices to determine the vector of coefficients nor forces us to drop small firms, due to the large number of firm effects to estimate.[17]

We recover estimates for the fixed effects for 406404 individuals and 31649 firms. In the appendix, we include the distribution of the worker fixed effects (Figure A2) and firm fixed effects (Figure A3) for the largest connected group.

With estimates of worker types at hand, we now proceed to construct measures of the average worker type and dispersion of worker type at the firm level. Specifically, we construct the variables $AvWorkerType_{jt}$, $SdWorkerType_{jt}$ and $\text{IQR}\,WorkerType_{jt}$ as:

$$\begin{aligned} AvWorkerType_{jt} &= \frac{1}{n_{jt}} \sum_{i \in I_{jt}} \theta_i \\ SdWorkerType_{jt} &= \frac{1}{n_{jt}} \sqrt{\sum_{i \in I_{jt}} \left(\theta_i - AvWorkerType_{jt}\right)^2} \\ \text{IQR}\,WorkerType_{jt} &= \theta^{j,75th} - \theta^{j,25th} \end{aligned}$$

where $I_{jt}$ is the set of workers employed by firm $j$ at time $t$, $\theta^{j,75th}$ and $\theta^{j,25th}$ are the types of the workers at the 75th and 25th percentile of firm $j$'s employees type distribution.

[17]The number of firms' fixed effect is too large for e.g. the *felsdv* estimator. In such case, Andrews et al. (2006) suggest pooling small plants into a single superplant. However, we prefer not to implement a similar strategy, as, in our case, firms - not plants - are the units of observation.

We build these measures only for firms with at least 4 sampled workers. Such threshold is a compromise between retaining a sample of satisfactory size and constructing sample measures that approximate the true underlying measures. On the one hand, a larger threshold forces us to cut a larger percentage of the sample. On the other hand, a larger number of sampled workers reduces the noise in the estimation of a firm's matching set. If no complementarity in production exists between workers,[18] a firm selects each worker independently from the others. Then, each employment relation is a realization of a match along the set of acceptable matches within a firm's matching set. In the limit, increasing the number of match realizations, the constructed statistics of worker types converges to the true measure. Choosing a higher threshold does not affect the results. If including firms with less than 4 sampled workers, instead, the coefficients on our variables of interest are of the correct sign but in some specifications might not be significant.

### 3.4 Firm types

For the purpose of comparing matching choices of exporting and non-exporting firms, we need to control for the type of the firm. Eeckhout & Kircher (2011) show that the relationship between true firm type and firm fixed effects estimated from a AKM-style wage regression is theoretically ambiguous, i.e. it can be positive, negative or zero. Eeckhout & Kircher (2011) also argue that the ideal firm component is a measure of firm type that is specific to every job within the firm, but measurable variables such as output and profits are obviously only observed at the aggregate firm level, not for each relationship within the firm. We therefore adopt three proxies for firm type to investigate the behaviour of firms fixed effects $\psi$: value added per worker of firm $j$, $VApw_j$, the logarithm of total employment in firm $j$, $\log Emp_j$ and share in the domestic market $DomShare_j$,

[18] This assumption, although very restrictive, allows us to map the model to the data. In addition, it is necessary for tractability. It is not obvious to us how to approach sorting problems with three agents in presence of search costs other than in a very simplified framework.

defined as the ratio of firm $j$'s domestic sales to total domestic sales in the firm's sector (each firm is classified as belonging to only one sector in each year).[19] While the first two proxies are standard measures of the productivity or demand intensity for a firm product, the third is motivated by Eaton et al. (2011). In particular, while the first two proxies contain a measure of success over all markets, including the foreign ones, the third variable better captures the success of the firm with respect to the domestic market, *before* the choice of exporting. We average each proxy over the years the firm appears in the sample to smooth out the effect of changes in the workforce.[20]

We first explore the hypothesis put forward by EK regarding the ability of the AKM firm fixed effects to capture the firm type. Table 1 shows the pairwise correlation between the AKM firm fixed effect, the three proxies for firm type and the average worker type at firm $j$ as measured by the average AKM worker fixed effect, $AvWorkerType_j$ over the sample period at firm $j$. The first striking fact is the negative and large correlation ($-0.69$) between average worker type and the AKM firm fixed effects $\psi$, confirming previous findings by Abowd et al. (2004). If instead we employ the three proxies for firm type, we observe for each of them a positive and significant correlation with the average worker type of roughly similar magnitude. The three firm type proxies are in turn all positively correlated with one another, but display small and opposite correlations with the AKM fixed effect $\psi$. In particular $DomShare_j$ and $VApw_j$ have a positive correlation of 0.03 and of 0.01 with $\psi$, respectively, while and $\log Emp_j$ displays a negative correlation of $-0.01$.

Table 2 shows that this correlation pattern is not unique to a few sectors. In column 4 we report the correlation between $AvWorkerType_j$ and $\psi_j$ by two-digit sector, while column 6 displays the

[19] We consider sectors at the 4-digit level for the constructions of market shares.

[20] Our model confirms the positive correlation between productivity, value added per worker and domestic market share. According to our theory, more productive firms tend to match with better workers, realizing on average larger revenues. Therefore, firms of higher productivity should display larger value added per worker and a larger share in the domestic market. The model is silent about employment differences due to variations in productivity. In fact, we focus exclusively on the production relation between one firm and one worker. If introducing homogeneous labour in the production function, the model will also address the implication that more productive firms hire a larger workforce.

analogous correlation between $DomShare_j$ and $AvWorkerType_j$. While the first set of correlations is always negative and significant, the second set of correlations is positive and significant in most cases. The evidence presented in tables 1 and 2 is consistent with the hypothesis put forward by EK, that the AKM firm fixed effect may not be correlated with the true firm type, although it is still possible that, as Abowd et al. (2004), there is truly negative assortative matching between workers and firms.

### 3.5 Empirical specification 1: export status and matching set

We now proceed to illustrate the specifications employed to describe the different matching behavior of exporting and non-exporting firms. The first implication of our model is that exporting firms hire workers of higher average type. This is a similar prediction to the models of Sampson (2012) and, under the interpretation of permanent worker heterogeneity, Helpman et al. (2010). We believe this is a novel method of corroborating such prediction since it shows directly that an exporter pays higher wages *because* it employs better workers, not because it shares higher revenues with the same type of workers. The former is the mechanism involved in explaining the exporter wage premium in Helpman et al. (2010), but we believe it has not been tested before.

In a pooled cross-section of firms over the sample period, the basic specification we employ is the following:

$$AvWorkerType_{jt} = \beta_0 + \beta_1 Export_{jt} + \beta_2 \ Firm \ Type_{jt} + D_{ind,t} + u_{jt} \tag{9}$$

where $Export_{jt} = 1$ if firm $j$ exports at time $t$ and $Firm\ Type_{jt}$ is one or all of the three proxies for firm productivity, $VApw_j$, $\log Emp_j$ and $DomShare_j$.

Differences in average worker type between exporters and non-exporters might mainly reflect

differences in the occupational structure. If, for example, exporters employ workers in occupations with higher average wage, they might also have higher average type, since the person effect contains all time-invariant characteristics, like occupation that rarely changes over time for a given worker.[21] We add the number of occupation, $N.occ_{jt}$ and the share of white collar workers,[22] *white share*, to specification (9). Similarly, the number of exported products, log $Products$, which we include in the specification with all controls, is intended to capture structural differences in occupational complexity that might cause a spurious correlation of the exporting status with the average firm type.

In addition, all specifications but the first include a quadratic in the number of sampled workers to control for the precision of our left-hand side estimates. Finally, the specifications includes sector-year dummies, $D_{st}$.

The novel contribution of this paper is the prediction that exporters match with workers that are characterized by lower *relative* dispersion of ability. The specification that we employ is the following:

$$SdWorkerType_{jt} = \beta_0' + \beta_1' Export_{jt} + \beta_2' Firm\ Type_{jt} + D_{st} + u_{jt}'. \tag{10}$$

The theoretical section shows that the only robust prediction regarding the link between worker type dispersion and export status (and productivity) requires expressing such dispersion either in percentage terms or relative to the average worker type. In this regard, it is essential to remember that the fixed effects are estimated from a log-linearized equation, where types are therefore already expressed in percentage differences from one another. Nevertheless we will add the average worker

[21] Around 80% of the workers in the sample do not switch occupation during the time period analyzed.

[22] The blue vs white collar classification is based on occupational code. We report the classification we adopt in Table A3.

type in the specification with all controls.

Similarly to specification (9), we include the number of occupation, $N.occ_{jt}$, the share of white collar workers, white share and the number of exported products, log $Products$, to control for differences in the occupational structure across firms with different export status.

All specifications include sector-year dummies, $D_{st}$.

Both specifications (9) and (10) are estimated by OLS and standard errors are clustered at the level of the firm.

### 3.5.1 Results

The estimation results relative to specifications (9) and (10) are presented in Tables 3 and 4. Column 1 of Table 3 reports a positive and statistically significant relationship between export status and the average type of the worker employed by the firm. The positive relationship is of similar strength when we introduce in turn the three controls for firm type (domestic share, value added per worker and employment).

As predicted by theory, the coefficient on all three proxies for firm type is positive and significant, like the one on export status. In the specification reported in column 4 we include the three controls for firm type in the same regression, and the coefficient on export (the one of our interest) remains positive and significant, like the ones on value added per worker and employment.

Table 4 reports the results of the estimation of specification (10) and has a similar structure to Table 3. Starting from column 1 where no controls are added, we document the expected negative and significant relationship between export status and variability of worker type. The effect persists with a similar magnitude when we control for the above mentioned firm type controls (domestic share and value added per worker). When we control for the employment level of the firm, we obtain a negative but not significant coefficient (columns 2 and 5). However, the inclusion of all

the control variables in column (6) restores the expected negative and significant coefficient on the export dummy. Interestingly, while, as predicted by theory, the coefficient on two proxies for firm type is negative (columns 2 and 3), the table documents a positive and significant correlation between value added per worker and the dispersion of worker type (column 4 - 6) a pattern that is not in line with the predictions of the model.

It is important to quantify the effect at the core of this paper. Based on our preferred specification in Table 4, column 6 where we include all controls, the expected difference on the dispersion of worker type between exporter and non-exporter firms is about 0.019 points (holding the other variables constant). Considered that the dependent variable has a standard deviation of 0.41, an exporter features worker variability that is lower by 4.6% standard deviations. The effect on the mean worker type can be calculated using the results from Table 3 and is of the same order of magnitude, but a little smaller: an exporting firm displays an average worker type that is 4.3% standard deviations higher.[23]

Tables 5 and 6 report estimates for the same specifications as in tables 3 and 4, but employ a different proxy for the worker type, i.e. their average wage over the entire sample period and across all firms. This is a strategy for approximating the ability of the worker that is supported theoretically by Eeckhout & Kircher (2011) and that we employ to check for robustness. Table 5 reports again a positive relationship between export status and average worker type, which holds with the same magnitude when we control for firm type controls and occupation structure (columns 2, 3 and 4). The coefficient on export status reduces a bit in the last specification when we include all control variables (and in particular the number of product exported). Similarly, Table 6 confirms a negative relationship between the dispersion of worker type and export status (when significant, the

[23]This magnitude has been computed by using export coefficient of Table 3 column 5. The standard deviation of the average worker type is 0.81.

coefficient on export status is negative). Controlling for the type of the firm (by using employment, domestic market share and value added per worker) the coefficient on export is negative and once again we find that firms with higher employment and higher domestic share have tighter worker type dispersion - coherently with the model. But, again, firms with high value added per worker have a wider variation of worker type (which contrasts with theoretical predictions).

Tables 7 and 8 present robustness checks where specification (10) is estimated for different groups of workers. In particular, we divide occupations into 'white' and 'blue' collar (as reported in Table (A3)). Table 7 reports results for white collar workers and Table 8 for blue collar workers. The coefficient on the export dummy is always negative and significant for both groups, although the level of significance tends to be higher for the group of blue collar workers. This is perhaps due to the higher share of blue collar workers and therefore larger sample available for the estimation. Interestingly, if we compare coefficients on firm's type controls (columns 2, 3 and 4 in Tables 7 and 8) we discover that for both white and blue collar regressions, employment and domestic market share have the expected sign, i.e. they are negatively related with the standard deviation of workers types. Conversely, the coefficient on value added per worker is significant only in the blue collar regression; suggesting that the 'puzzling' effect discussed above for tables 4 and 6 comes exclusively from the blue collar sample.

Table 9 presents a further robustness of the result to the definition of worker type employed as dependent variable. In particular, we employ the interquartile range of worker type at firm $j$, as described earlier. It is easy to verify that all previously described patterns appear again in this table. Exporting firms choose a narrower range of worker types.

### 3.6 Empirical specification 2: market access and tariff shocks

Our first empirical strategy has relied on cross-sectional differences between exporting and non-exporting firms. Plausibly, the export dummy may be capturing the effect of other firms characteristics that are not included in our firm type proxies and that affect the matching behavior of firms.

Our second strategy to detect the impact of exporting on matching between firms and workers aims at addressing this concern. We exploit differences in the opportunities offered by foreign markets, approximated by demand shocks and tariffs across sectors and countries over time or because of variations in tariffs. These different shocks, which we indicate as 'market access' should affect exporting firms differentially from non-exporting firms. A positive demand shock in a foreign market or a lower tariff faced by French exporters should induce the exporting firm to select an even less dispersed labor force. The specification that we estimate is the following:

$$\begin{aligned} AvWorkerType_{jt} &= \gamma_0 + \gamma_1 Mkt\ Access_{st} \times Export_{jt} + \gamma_2 Mkt\ Access_{st} \\ &\quad + \gamma_3 Export_{jt} + D_{st} + v_{jt}, \qquad (11) \\ SdWorkerType_{jt} &= \gamma_0' + \gamma_1' Mkt\ Access_{st} \times Export_{jt} + \gamma_2' Mkt\ Access_{st} \\ &\quad + \gamma_3' Export_{jt} + D_{st} + v_{jt}' \qquad (12) \end{aligned}$$

where

$$MktAccess_{st} = \sum_r MktAccess_{srt} \times \frac{French\ exports_{sr,t-1}}{French\ exports_{s,t-1}}\ , \tag{13}$$

$$MktAccess_{srt} = \begin{cases} Tariffs_{srt} & \text{or} \\ Imports_{srt} & \text{or} \\ \frac{Imports_{srt}}{Tariffs_{srt}} & \end{cases},$$

$Imports_{srt}$ is the total value of imports by country $r$ from the rest of the world[24], $Tariffs_{srt}$ is the tariff faced by a French firm exporting to country $r$ in sector $s$ at time $t$, and $French\ exports_{sr,t-1}$ is the value of exports from France to country $r$ in sector $s$ at time $t-1$ (with total exports in the sector in that year indicated as $French\ exports_{s,t-1}$). The variable $MktAccess_{st}$ measures cost of access or demand size in foreign markets for firms in a given sector $s$, weighted by the importance for French firms in that sector in the previous year. The model predicts that a good export opportunity should result in an increase in the average worket type and further tightening of the acceptance set for an exporting firm, so we expect $\gamma_1 < 0$ and $\gamma_1' > 0$ for the case of $MktAccess_{srt} = Tariffs_{srt}$ and the opposite when market access is measured as $Imports_{srt}$ or $\frac{Imports_{srt}}{Tariffs_{srt}}$. [25]

### 3.6.1 Results

Tables 10 and 11 report estimates of the coefficients in specifications (11) and (12) when market access for a firm in sector $s$ is measured by the average tariff faced by an exporter in sector $s$. All columns of Table 10 report a negative coefficient $\gamma_1$ - which is line with the prediction - but unfortunately not statistically significant.

In Table 11 we find for all specifications that the estimated coefficient $\gamma_1'$ is positive and signifi-

[24] The inclusion of French exports to country $r$ does not affect the results.

[25] We also construct a market access variable at the level of the firm using previous year's exports as weights.

cant, so that exporters seem to choose a less dispersed workforce in particular when having better access to foreign markets. The inclusion of firm type controls does not affect the magnitude and significance of this result. Coefficient on export status is negative and significant in all specifications. If evaluated at the mean of $Tariffs_{srt}$ - 5.58% - an exporter features worker variability that is lower by 3.6% standard deviations than a non-exporter firm (which is in line with the quantification reported in section 3.5.1).

Table 12 and 13 report estimates of the coefficients in specifications (11) and (12) when market access for a firm in sector $s$ is measured by total demand for imports faced by an exporter in sector $s$ as in equation (13). We do not present results for the case when total import demand is deflated by the tariff faced by French exporters because they are very similar. Table 12 reports results on the average worker type, but our coefficient of interest is not significant.

Table 13 reports very similar results to Table 11: better export market conditions as measured by a larger import demand result in a tighter matching set for exporting firms. So, contrary to Table 12, the effect of export opportunities on standard deviation of worker type is robust to the definition of market access. In particular, firms exporting in country-sector with 'mean' market access (mean value equal to 13 in our sample) have a slightly lower worker variability than non-exporters (0.2% standard deviation units), with such gap increasing with the market access of the firm.

As a final robustness check we build a measure of market access at firm level. In particular we replicated the measure on the demand for imports for the markets in which the firm is an active exporter. Results in table A6 refer to average worker type by firm and show a null coefficient on the interaction between the export status and firms specific market access. More interestingly, results in Table A7 confirm our previous findings: firms exporting in markets experiencing positive

demand shock have tighter worker type dispersion.

# 4 Conclusions

Using linked employer-employee data from France, we show that exporters and non-exporters match with sets of workers that are different. Exporters employ workers of higher type and lower dispersion. We rationalize this finding using a model of matching with search frictions where more productive firms and exporting firms match with better workers and tolerate a lower degree of dispersion among the workers employed.

In this paper we have not discussed the consequences of our results in terms of welfare. Our model only predicts that exporting firms tolerate less relative dispersion in worker type, but it does not analyze what happens to exporting and non-exporting firms relative to their autarky matching decisions. In theory the model features two counteracting effects. While newly exporting firms have higher incentives to tighten their matching range, non-exporting firms see their revenues decline because of import competition and therefore will see an increase in their normalized matching range. Hence the model is currently in a very simple partial equilibrium set up, which cannot be used for welfare analysis. In separate work we build a symmetric infinite horizon two-country model where the distribution of firm types for both exporting and non-exporting firms is estimated from the data. The model endogenizes prices, expenditures and the distribution of unmatched firms and workers in every period. In order to gauge the effect of trade on matching we derive gains from trade as a function of the size of the search cost. In preliminary results we find that the gains from trade are an increasing function of the cost of search. When the economy features very low search costs matching is already very close to the optimum, so there are no additional gains from better matching, but as the cost $c$ increases trade brings about a tightening of the matching bands for a

sufficiently high number of exporters and welfare increases as a result.

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Table 1: *Rank Correlation Matrix*, proxies for firms' types

| | $\psi$ | Avg. Worker | Avg.Dom. Share | Avg.VA per w. | Avg. Empl. |
|---|---|---|---|---|---|
| $\psi$ | 1 | | | | |
| Avg. Worker Type by Firm | -0.69 | 1 | | | |
| Avg. Dom. Share | 0.03 | 0.06 | 1 | | |
| Avg. VA per worker | 0.01 | 0.04 | 0.63 | 1 | |
| Avg. Empl. | -0.01 | 0.04 | 0.64 | 0.90 | 1 |

$\psi$: Firms' fixed effects, from the AKM decomposition.
*Avg. Worker Type by Firm*: Average of workers' fixed effects by firm, from the AKM decomposition.
*Avg. VA per worker*: Average value added per worker, normalized by 4-digit industries.
*Avg. Dom. Share*: Average domestic market share at a 4-digit level.
*Avg. Empl.*: Average employment, normalized by 4-digit industries.
*Notes*: Rank correlation between proxies of firms types. We do not report the p-values but all rank correlations are significantly different from zero.

Table 2: Measuring Sorting Patterns, Manufacturing Sectors

| NAF | Industry Label | No Firms | (4) $\psi$, $Avg. Worker$ $\rho_S$[1] | (5) p-val[2] | (6) $Avg.$ Share, $Avg. Worker$ $\rho_S$[1] | (7) p-val[2] |
|---|---|---|---|---|---|---|
| 10 | Food | 15 | -0.93 | 0.00 | 0.30 | 0.28 |
| 11 | Beverage | 12 | -0.70 | 0.00 | 0.10 | 0.77 |
| 12 | Tobacco prods | - | - | - | - | - |
| 13 | Textiles | - | - | - | - | - |
| 14 | Clothing | 518 | -0.63 | 0.00 | 0.11 | 0.01 |
| 15 | Leather/shoes | - | - | - | - | - |
| 17 | Paper | 1971 | -0.74 | 0.00 | 0.02 | 0.28 |
| 18 | Printing | 2064 | -0.72 | 0.00 | 0.04 | 0.10 |
| 19 | Refining | 606 | -0.81 | 0.00 | -0.01 | 0.79 |
| 20 | Chemical | 1180 | -0.65 | 0.00 | 0.10 | 0.00 |
| 21 | Pharma | 999 | -0.68 | 0.00 | 0.08 | 0.01 |
| 22 | Plastics | 2897 | -0.63 | 0.00 | 0.06 | 0.00 |
| 23 | Non-metallic prods | 74 | -0.61 | 0.00 | 0.17 | 0.15 |
| 24 | Metalworking | 1887 | -0.66 | 0.00 | 0.15 | 0.00 |
| 25 | Metal prods | 2510 | -0.73 | 0.00 | 0.08 | 0.00 |
| 26 | Info/elec/opt | 1421 | -0.68 | 0.00 | 0.06 | 0.02 |
| 27 | Elec equip | 745 | -0.78 | 0.00 | 0.04 | 0.29 |
| 28 | Machinery | 7473 | -0.71 | 0.00 | 0.08 | 0.00 |
| 29 | Automotive | 3764 | -0.73 | 0.00 | 0.08 | 0.00 |
| 30 | Other trans equip | 171 | -0.72 | 0.00 | -0.02 | 0.77 |
| 31 | Furniture | 1269 | -0.69 | 0.00 | 0.08 | 0.01 |
| 32 | Other mfg | 1098 | -0.64 | 0.00 | 0.04 | 0.20 |
| 33 | Repairs | 1632 | -0.70 | 0.00 | 0.09 | 0.00 |
| | Manufacturing | 32317 | -0.69 | 0.00 | 0.06 | 0.00 |

[1] Spearman correlation coefficient.
[2] p-value from testing independence between the variables.

*Notes*: Columns (4)-(5): Rank correlation and significance level between the average worker type, ($Avg. Worker$), and the firm fixed effect ($\psi$) from an AKM decomposition including a quartic polynomial in experience, a dummy for workers residing in Ile-de-France, time dummies and all the interactions with the gender dummy.

Columns (6)-(7): Rank correlation and significance level between the average worker type, ($Avg. Worker$), and the firm type, proxied by the average domestic market share in 4-digit sectors $Avg.$ Share.

Table 3: Pooled Cross-sectional Regressions: *Average workers' type*, at least 4 workers

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Variables | Average of Workers' Fixed Effects, at least 4 workers | | | | | |
| Export | 0.083[a] | 0.045[b] | 0.044[b] | 0.045[b] | 0.037[c] | 0.025 |
| | (0.018) | (0.019) | (0.019) | (0.019) | (0.019) | (0.022) |
| N. Occ | | 0.021[a] | 0.024[a] | 0.024[a] | 0.019[a] | 0.003 |
| | | (0.004) | (0.003) | (0.003) | (0.004) | (0.004) |
| log *empl* | | 0.020[c] | | | 0.021[c] | 0.033[a] |
| | | (0.011) | | | (0.011) | (0.011) |
| log *dom.share* | | | 0.006[c] | | 0.001 | -0.001 |
| | | | (0.004) | | (0.004) | (0.004) |
| log *VA per worker* | | | | 0.065[a] | 0.066[a] | 0.020 |
| | | | | (0.013) | (0.013) | (0.013) |
| *white share* | | | | | | 0.429[a] |
| | | | | | | (0.029) |
| log *N. Products* | | | | | | 0.00437 |
| | | | | | | (0.007) |
| Constant | 0.781[c] | 0.589 | 0.677 | 0.338 | 0.285 | 0.398 |
| | (0.414) | (0.424) | (0.420) | (0.414) | (0.418) | (0.433) |
| Sector-Year | y | y | y | y | y | y |
| Observations | 87,949 | 87,949 | 87,949 | 87,949 | 87,949 | 87,949 |
| R-squared | 0.015 | 0.019 | 0.019 | 0.020 | 0.020 | 0.033 |

*N.Occ.*: number of occupations, based on 2 digit occupational codes for France.
log *empl.* log-employment.
log *VA per worker*: log-value added per worker.
log *dom.share*: log-domestic market share, at the 4 digit sector level.
*white share*: share of non-production workers.
log *N. Products*: log-number of exported products (HS6 codes). This variable is zero for non-exporters.
*Notes*: Cross-sectional Regressions for firms with at least 4 workers, years 1995-2007. Different specifications in the columns. Standard errors, clustered at the level of the firm, are reported in parenthesis. All specifications but the first include a quadratic in the number of sampled workers, to control for the precision of the left-hand side variable.

Table 4: Pooled Cross-sectional Regressions: *Standard Deviation*, at least 4 workers

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Variables | Standard Deviation of Workers' Fixed Effects, at least 4 workers | | | | | |
| Export | -0.014[c] | -0.001 | -0.022[a] | -0.034[a] | -0.007 | -0.018[c] |
| | (0.007) | (0.008) | (0.007) | (0.007) | (0.008) | (0.009) |
| N. Occ | | 0.035[a] | 0.017[a] | 0.014[a] | 0.034[a] | 0.030[a] |
| | | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| log *empl* | | -0.087[a] | | | -0.087[a] | -0.083[a] |
| | | (0.004) | | | (0.004) | (0.004) |
| log *dom.share* | | | -0.006[a] | | 0.002 | 0.001 |
| | | | (0.001) | | (0.001) | (0.001) |
| log *VA per worker* | | | | 0.041[a] | 0.036[a] | 0.024[a] |
| | | | | (0.005) | (0.005) | (0.005) |
| *white share* | | | | | | 0.159[a] |
| | | | | | | (0.012) |
| log *N. Products* | | | | | | 0.006[b] |
| | | | | | | (0.003) |
| Avg Worker Type | | | | | | -0.0802[a] |
| | | | | | | (0.004) |
| Constant | 0.614[a] | 0.779[a] | 0.525[a] | 0.370[a] | 0.624[a] | 0.702[a] |
| | (0.102) | (0.120) | (0.108) | (0.103) | (0.119) | (0.129) |
| Sector-Year | y | y | y | y | y | y |
| Observations | 87,949 | 87,949 | 87,949 | 87,949 | 87,949 | 87,949 |
| R-squared | 0.040 | 0.059 | 0.045 | 0.046 | 0.060 | 0.090 |

*N.Occ.*: number of occupations, based on 2 digit occupational codes for France.
log *empl.* log-employment.
log *VA per worker*: log-value added per worker.
log *dom.share*: log-domestic market share, at the 4 digit sector level.
*white share*: share of non-production worker.
log *N. Products*: log-number of exported products (HS6 codes). This variable is zero for non-exporters.
*Avg Worker Type*: average worker fixed effect, estimated by the AKM decomposition, by firm.
*Notes*: Cross-sectional Regressions for firms with at least 4 workers, years 1995-2007. Different specifications in the columns. Standard errors, clustered at the level of the firm, are reported in parenthesis. All specifications but the first include a quadratic in the number of sampled workers, to control for the precision of the left-hand side variable.

Table 5: Pooled Cross-sectional Regressions: *Average Lifetime Wage*, at least 4 workers

| Variables | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Average of lifetime Workers' Wage, at least 4 workers | | | | | |
| Export | $0.135^a$ | $0.058^a$ | $0.056^a$ | $0.066^a$ | $0.034^a$ | $0.024^b$ |
| | (0.008) | (0.008) | (0.008) | (0.008) | (0.008) | (0.009) |
| N. Occ | | $0.022^a$ | $0.035^a$ | $0.037^a$ | $0.017^a$ | $-0.003^c$ |
| | | (0.002) | (0.002) | (0.001) | (0.002) | (0.002) |
| log *empl* | | $0.084^a$ | | | $0.084^a$ | $0.099^a$ |
| | | (0.005) | | | (0.005) | (0.005) |
| log *dom.share* | | | $0.023^a$ | | $0.004^b$ | $0.003^c$ |
| | | | (0.002) | | (0.002) | (0.002) |
| log *VA per worker* | | | | $0.176^a$ | $0.176^a$ | $0.117^a$ |
| | | | | (0.007) | (0.007) | (0.007) |
| *white share* | | | | | | $0.552^a$ |
| | | | | | | (0.014) |
| log *N. Products* | | | | | | 0.002 |
| | | | | | | (0.003) |
| Constant | $9.561^a$ | $9.137^a$ | $9.489^a$ | $8.544^a$ | $8.354^a$ | $8.484^a$ |
| | (0.174) | (0.157) | (0.174) | (0.195) | (0.203) | (0.184) |
| Sector-Year | y | y | y | y | y | y |
| Observations | 88,813 | 88,813 | 88,813 | 88,813 | 88,813 | 88,813 |
| R-squared | 0.107 | 0.155 | 0.151 | 0.176 | 0.189 | 0.259 |

*N.Occ.*: number of occupations, based on 2 digit occupational codes for France.
log *empl.* log-employment.
log *VA per worker*: log-value added per worker.
log *dom.share*: log-domestic market share, at the 4 digit sector level.
*white share*: share of non-production worker.
log *N. Products*: log-number of exported products (HS6 codes). This variable is zero for non-exporters.
*Notes*: Cross-sectional Regressions for firms with at least 4 workers, years 1995-2007. Different specifications in the columns. Standard errors, clustered at the level of the firm, are reported in parenthesis. All specifications but the first include a quadratic in the number of sampled workers, to control for the precision of the left-hand side variable.

Table 6: Pooled Cross-sectional Regressions: *Standard Deviation*, at least 4 workers

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Variables | Standard Deviation of lifetime Workers' Wage, at least 4 workers | | | | | |
| Export | -0.014[c] | 0.003 | -0.021[a] | -0.033[a] | -0.003 | -0.006 |
| | (0.007) | (0.007) | (0.007) | (0.007) | (0.007) | (0.006) |
| N. Occ | | 0.038[a] | 0.017[a] | 0.014[a] | 0.037[a] | 0.030[a] |
| | | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| log *empl* | | -0.099[a] | | | -0.100[a] | -0.027[a] |
| | | (0.004) | | | (0.004) | (0.003) |
| log *dom.share* | | | -0.006[a] | | 0.002[c] | 0.003[a] |
| | | | (0.001) | | (0.001) | (0.001) |
| log *VA per worker* | | | | 0.045[a] | 0.040[a] | 0.114[a] |
| | | | | (0.005) | (0.005) | (0.005) |
| *white share* | | | | | | 0.493[a] |
| | | | | | | (0.010) |
| log *N. Products* | | | | | | 0.012[a] |
| | | | | | | (0.002) |
| Avg Wage (Sq.) | | | | | | -0.730[a] |
| | | | | | | (0.007) |
| Constant | 0.668[a] | 0.874[a] | 0.584[a] | 0.415[a] | 0.710[a] | 6.951[a] |
| | (0.161) | (0.180) | (0.168) | (0.160) | (0.176) | (0.131) |
| Sector-Year | y | y | y | y | y | y |
| Observations | 88,813 | 88,813 | 88,813 | 88,813 | 88,813 | 88,813 |
| R-squared | 0.036 | 0.059 | 0.041 | 0.042 | 0.061 | 0.516 |

*N.Occ.*: number of occupations, based on 2 digit occupational codes for France.
log *empl.* log-employment.
log *VA per worker*: log-value added per worker.
log *dom.share*: log-domestic market share, at the 4 digit sector level.
*white share*: share of non-production worker.
log *N. Products*: log-number of exported products (HS6 codes). This variable is zero for non-exporters.
*Avg Wage*: average lifetime wage at the firm-level.
*Notes*: Cross-sectional Regressions for firms with at least 4 workers, years 1995-2007. Different specifications in the columns. Standard errors, clustered at the level of the firm, are reported in parenthesis. All specifications but the first include a quadratic in the number of sampled workers, to control for the precision of the left-hand side variable.

Table 7: Pooled Cross-sectional Regressions: *Standard Deviation* white collar workers, at least 4 workers

| Variables | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Standard Deviation of Workers' Fixed Effects, at least 4 workers | | | | | |
| Export | -0.056[b] | -0.044[c] | -0.055[b] | -0.062[a] | -0.048[b] | -0.056[b] |
| | (0.024) | (0.024) | (0.024) | (0.024) | (0.024) | (0.026) |
| N. Occ | | 0.013[a] | -0.000 | -0.001 | 0.013[a] | 0.018[a] |
| | | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| log *empl* | | -0.058[a] | | | -0.060[a] | -0.041[a] |
| | | (0.006) | | | (0.006) | (0.007) |
| log *dom.share* | | | -0.004[b] | | 0.003 | 0.003 |
| | | | (0.002) | | (0.002) | (0.002) |
| log *VA per worker* | | | | 0.011 | 0.006 | -0.002 |
| | | | | (0.008) | (0.008) | (0.008) |
| *white share* | | | | | | 0.200[a] |
| | | | | | | (0.022) |
| log *N. Products* | | | | | | 0.006 |
| | | | | | | (0.004) |
| Avg Worker Type | | | | | | -0.067[a] |
| | | | | | | (0.008) |
| Constant | 0.530[a] | 0.722[a] | 0.478[a] | 0.462[a] | 0.728[a] | 0.570[a] |
| | (0.104) | (0.134) | (0.105) | (0.113) | (0.143) | (0.128) |
| Sector-Year | y | y | y | y | y | y |
| Observations | 30,186 | 30,186 | 30,186 | 30,186 | 30,186 | 30,186 |
| R-squared | 0.131 | 0.141 | 0.134 | 0.134 | 0.141 | 0.159 |

*N.Occ.*: number of occupations, based on 2 digit occupational codes for France.
log *empl.* log-employment.
log *VA per worker*: log-value added per worker.
log *dom.share*: log-domestic market share, at the 4 digit sector level.
*white share*: share of non-production worker.
log *N. Products*: log-number of exported products (HS6 codes). This variable is zero for non-exporters.
*Avg Worker Type*: average worker fixed effect, estimated by the AKM decomposition, by firm.
*Notes*: Cross-sectional Regressions for firms with at least 4 workers, years 1995-2007. Different specifications in the columns. Standard errors, clustered at the level of the firm, are reported in parenthesis. All specifications but the first include a quadratic in the number of sampled workers, to control for the precision of the left-hand side variable.

Table 8: Pooled Cross-sectional Regressions: *Standard Deviation* blue collar workers, at least 4 workers

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Variables | Standard Deviation of Workers' Fixed Effects, at least 4 workers | | | | | |
| Export | -0.046[a] | -0.028[a] | -0.042[a] | -0.056[a] | -0.028[a] | -0.032[a] |
| | (0.008) | (0.009) | (0.009) | (0.009) | (0.009) | (0.011) |
| N. Occ | | 0.022[a] | 0.006[a] | 0.003[b] | 0.021[a] | 0.022[a] |
| | | (0.002) | (0.001) | (0.001) | (0.002) | (0.002) |
| log *empl* | | -0.077[a] | | | -0.075[a] | -0.071[a] |
| | | (0.005) | | | (0.005) | (0.006) |
| log *dom.share* | | | -0.009[a] | | -0.003 | -0.003[c] |
| | | | (0.001) | | (0.001) | (0.001) |
| log *VA per worker* | | | | 0.020[a] | 0.026[a] | 0.028[a] |
| | | | | (0.006) | (0.006) | (0.006) |
| *white share* | | | | | | 0.005 |
| | | | | | | (0.022) |
| log *N. Products* | | | | | | 0.005 |
| | | | | | | (0.003) |
| Avg Worker Type | | | | | | -0.088[a] |
| | | | | | | (0.005) |
| Constant | 0.578[a] | 0.677[a] | 0.456[a] | 0.428[a] | 0.551[a] | 0.613[a] |
| | (0.111) | (0.145) | (0.133) | (0.118) | (0.142) | (0.180) |
| Sector-Year | y | y | y | y | y | y |
| Observations | 62,522 | 62,522 | 62,522 | 62,522 | 62,522 | 62,522 |
| R-squared | 0.033 | 0.045 | 0.035 | 0.034 | 0.045 | 0.072 |

*N.Occ.*: number of occupations, based on 2 digit occupational codes for France.
log *empl.* log-employment.
log *VA per worker*: log-value added per worker.
log *dom.share*: log-domestic market share, at the 4 digit sector level.
*white share*: share of non-production worker.
log *N. Products*: log-number of exported products (HS6 codes). This variable is zero for non-exporters.
*Avg Worker Type*: average worker fixed effect, estimated by the AKM decomposition, by firm.
*Notes*: Cross-sectional Regressions for firms with at least 4 workers, years 1995-2007. Different specifications in the columns. Standard errors, clustered at the level of the firm, are reported in parenthesis. All specifications but the first include a quadratic in the number of sampled workers, to control for the precision of the left-hand side variable.

Table 9: Pooled Cross-sectional Regressions: *Inter-quartile Range*, at least 4 workers

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Variables | Inter-quartile of Workers' Fixed Effects, at least 4 workers | | | | | |
| Export | -0.054[a] | -0.043[a] | 0.003 | -0.032[b] | -0.051[a] | -0.027[c] |
| | (0.013) | (0.013) | (0.013) | (0.013) | (0.013) | (0.015) |
| N. Occ | | -0.006[a] | 0.024[a] | -0.004[c] | -0.008[a] | 0.013[a] |
| | | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| log *empl* | | | -0.143[a] | | | -0.138[a] |
| | | | (0.006) | | | (0.006) |
| log *dom.share* | | | | -0.008[a] | | 0.002 |
| | | | | (0.002) | | (0.002) |
| log *VA per worker* | | | | | 0.072[a] | 0.034[a] |
| | | | | | (0.009) | (0.009) |
| *white share* | | | | | | 0.321[a] |
| | | | | | | (0.020) |
| log *N. Products* | | | | | | 0.010[b] |
| | | | | | | (0.0043) |
| Avg Worker Type | | | | | | -0.102[a] |
| | | | | | | (0.006) |
| Constant | 0.833[a] | 0.914[a] | 1.306[a] | 0.865[a] | 0.594[a] | 1.173[a] |
| | (0.247) | (0.229) | (0.257) | (0.240) | (0.220) | (0.277) |
| Sector-Year | y | y | y | y | y | y |
| Observations | 71,370 | 71,370 | 71,370 | 71,370 | 71,370 | 71,370 |
| R-squared | 0.053 | 0.054 | 0.074 | 0.055 | 0.058 | 0.107 |

*N.Occ.*: number of occupations, based on 2 digit occupational codes for France.
log *empl.* log-employment.
log *VA per worker*: log-value added per worker.
log *dom.share*: log-domestic market share, at the 4 digit sector level.
*white share*: share of non-production worker.
log *N. Products*: log-number of exported products (HS6 codes). This variable is zero for non-exporters.
*Avg Worker Type*: average worker fixed effect, estimated by the AKM decomposition, by firm.
*Notes*: Cross-sectional Regressions for firms with at least 4 workers, years 1995-2007. Different specifications in the columns. Standard errors, clustered at the level of the firm, are reported in parenthesis. All specifications but the first include a quadratic in the number of sampled workers, to control for the precision of the left-hand side variable.

Table 10: Tariff Regressions: *Average*, at least 4 workers

| Variables | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Average of Workers' Fixed Effects, at least 4 workers | | | | | |
| Weighted Tariff*Export | -0.002 | -0.003 | -0.003 | -0.003 | -0.003 | -0.005[c] |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) |
| Weighted Tariff | 0.002 | 0.002 | 0.002 | 0.003 | 0.004 | 0.008[b] |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) |
| Export | 0.089[a] | 0.058[a] | 0.049[b] | 0.046[b] | 0.054[a] | 0.044[b] |
| | (0.019) | (0.019) | (0.020) | (0.020) | (0.019) | (0.021) |
| N. Occ | | 0.025[a] | 0.019[a] | 0.022[a] | 0.023[a] | 0.003 |
| | | (0.001) | (0.002) | (0.002) | (0.002) | (0.002) |
| log *empl* | | | 0.025[a] | | | 0.034[a] |
| | | | (0.005) | | | (0.006) |
| log *dom.share* | | | | 0.012[a] | | 0.004[c] |
| | | | | (0.002) | | (0.002) |
| log *VA per worker* | | | | | 0.067[a] | 0.019[b] |
| | | | | | (0.007) | (0.007) |
| *white share* | | | | | | 0.420[a] |
| | | | | | | (0.017) |
| log *N. Products* | | | | | | 0.001 |
| | | | | | | (0.003) |
| Sector-Year | y | y | y | y | y | y |
| Observations | 72,713 | 72,713 | 72,713 | 72,713 | 72,713 | 72,713 |
| R-squared | 0.015 | 0.020 | 0.020 | 0.020 | 0.021 | 0.034 |

*N.Occ.*: number of occupations, based on 2 digit occupational codes for France.
log *empl.* log-employment.
log *VA per worker*: log-value added per worker.
log *dom.share*: log-domestic market share, at the 4 digit sector level.
*white share*: share of non-production worker.
log *N. Products*: log-number of exported products (HS6 codes). This variable is zero for non-exporters.
*Notes*: Cross-sectional Regressions for firms with at least 4 workers, years 1995-2007. Different specifications in the columns. Standard errors, clustered at the level of the firm, are reported in parenthesis. All specifications but the first include a quadratic in the number of sampled workers, to control for the precision of the left-hand side variable.

Table 11: Pooled Cross-sectional Regressions: *Standard Deviation*, at least 4 workers

| Variables | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Standard Deviation of Workers' Fixed Effects, at least 4 workers | | | | | |
| Weighted Tariff*Export | 0.009[a] | 0.009[a] | 0.009[a] | 0.009[a] | 0.008[a] | 0.007[a] |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| Weighted Tariff | -0.016[a] | -0.015[a] | -0.015[a] | -0.016[a] | -0.014[a] | -0.012[a] |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.002) |
| Export | -0.054[a] | -0.068[a] | -0.040[a] | -0.063[a] | -0.071[a] | -0.054[a] |
| | (0.015) | (0.015) | (0.015) | (0.015) | (0.015) | (0.015) |
| N. Occ | | 0.015[a] | 0.035[a] | 0.016[a] | 0.014[a] | 0.029[a] |
| | | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| log *empl* | | | -0.087[a] | | | -0.085[a] |
| | | | (0.003) | | | (0.003) |
| log *dom.share* | | | | -0.005[a] | | 0.003[b] |
| | | | | (0.001) | | (0.001) |
| log *VA per worker* | | | | | 0.041[a] | 0.022[a] |
| | | | | | (0.005) | (0.004) |
| *white share* | | | | | | 0.167[a] |
| | | | | | | (0.013) |
| log *N. Products* | | | | | | 0.008[a] |
| | | | | | | (0.002) |
| Avg Worker Type | | | | | | -0.085[a] |
| | | | | | | (0.003) |
| Sector-Year | y | y | y | y | y | y |
| Observations | 72,713 | 72,713 | 72,713 | 72,713 | 72,713 | 72,713 |
| R-squared | 0.046 | 0.050 | 0.065 | 0.050 | 0.052 | 0.098 |

*N.Occ.*: number of occupations, based on 2 digit occupational codes for France.
log *empl.* log-employment.
log *VA per worker*: log-value added per worker.
log *dom.share*: log-domestic market share, at the 4 digit sector level.
*white share*: share of non-production worker.
log *N. Products*: log-number of exported products (HS6 codes). This variable is zero for non-exporters.
*Avg Worker Type*: average worker fixed effect, estimated by the AKM decomposition, by firm.
*Notes*: Cross-sectional Regressions for firms with at least 4 workers, years 1995-2007. Different specifications in the columns. Standard errors, clustered at the level of the firm, are reported in parenthesis. All specifications but the first include a quadratic in the number of sampled workers, to control for the precision of the left-hand side variable.

Table 12: Pooled Cross-sectional Regressions: *Average*, at least 4 workers

| Variables | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Average of Workers' Fixed Effects, at least 4 workers | | | | | |
| Market Access*Export | -0.004 | -0.005 | -0.005 | -0.005 | -0.005 | -0.003 |
| | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) |
| Market Access | 0.003 | 0.003 | 0.003 | 0.004 | 0.003 | -0.000 |
| | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) |
| Export | $0.128^b$ | $0.107^c$ | $0.103^c$ | 0.091 | 0.095 | 0.054 |
| | (0.057) | (0.058) | (0.057) | (0.058) | (0.058) | (0.059) |
| N. Occ | | $0.025^a$ | $0.019^a$ | $0.022^a$ | $0.023^a$ | 0.003 |
| | | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| log *empl* | | | $0.026^a$ | | | $0.034^a$ |
| | | | (0.006) | | | (0.006) |
| log *dom.share* | | | | $0.012^a$ | | 0.003 |
| | | | | (0.002) | | (0.002) |
| log *VA per worker* | | | | | $0.067^a$ | $0.018^b$ |
| | | | | | (0.008) | (0.008) |
| *white share* | | | | | | $0.410^a$ |
| | | | | | | (0.019) |
| log *N. Products* | | | | | | 0.003 |
| | | | | | | (0.004) |
| Constant | $1.865^a$ | $1.713^a$ | $1.619^a$ | $1.743^a$ | $1.336^a$ | $1.328^a$ |
| | (0.056) | (0.056) | (0.061) | (0.057) | (0.078) | (0.084) |
| Sector-Year | y | y | y | y | y | y |
| Observations | 67,185 | 67,185 | 67,185 | 67,185 | 67,185 | 67,185 |
| R-squared | 0.015 | 0.019 | 0.020 | 0.020 | 0.021 | 0.033 |

*N.Occ.*: number of occupations, based on 2 digit occupational codes for France.
log *empl.* log-employment.
log *VA per worker*: log-value added per worker.
log *dom.share*: log-domestic market share, at the 4 digit sector level.
*white share*: share of non-production worker.
log *N. Products*: log-number of exported products (HS6 codes). This variable is zero for non-exporters.
*Notes*: Cross-sectional Regressions for firms with at least 4 workers, years 1995-2007. Different specifications in the columns. Standard errors, clustered at the level of the firm, are reported in parenthesis. All specifications but the first include a quadratic in the number of sampled workers, to control for the precision of the left-hand side variable.

Table 13: Pooled Cross-sectional Regressions: *Standard Deviation*, at least 4 workers

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Variables | Standard Deviation of Workers' Fixed Effects, at least 4 workers | | | | | |
| Market Access*Export | -0.010[a] | -0.010[a] | -0.010[a] | -0.010[a] | -0.010[a] | -0.008[a] |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| Market Access | 0.012[a] | 0.012[a] | 0.012[a] | 0.012[a] | 0.012[a] | 0.010[a] |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| Export | 0.125[a] | 0.114[a] | 0.130[a] | 0.119[a] | 0.105[a] | 0.103[a] |
| | (0.039) | (0.038) | (0.037) | (0.038) | (0.037) | (0.032) |
| N. Occ | | 0.015[a] | 0.035[a] | 0.016[a] | 0.014[a] | 0.030[a] |
| | | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| log *empl* | | | -0.087[a] | | | -0.085[a] |
| | | | (0.003) | | | (0.003) |
| log *dom.share* | | | | -0.004[a] | | 0.004[a] |
| | | | | (0.001) | | (0.001) |
| log *VA per worker* | | | | | 0.045[a] | 0.024[a] |
| | | | | | (0.005) | (0.004) |
| *white share* | | | | | | 0.172[a] |
| | | | | | | (0.0156) |
| log *N. Products* | | | | | | 0.005[c] |
| | | | | | | (0.003) |
| Avg Worker Type | | | | | | -0.086[a] |
| | | | | | | (0.003) |
| Constant | 0.405[a] | 0.318[a] | 0.629[a] | 0.308[a] | 0.0638 | 0.577[a] |
| | (0.0389) | (0.0380) | (0.0355) | (0.0381) | (0.0578) | (0.0481) |
| Sector-Year | y | y | y | y | y | y |
| Observations | 67,185 | 67,185 | 67,185 | 67,185 | 67,185 | 67,185 |
| R-squared | 0.045 | 0.050 | 0.064 | 0.050 | 0.052 | 0.099 |

*N.Occ.*: number of occupations, based on 2 digit occupational codes for France.
log *empl.* log-employment.
log *VA per worker*: log-value added per worker.
log *dom.share*: log-domestic market share, at the 4 digit sector level.
*white share*: share of non-production worker.
log *N. Products*: log-number of exported products (HS6 codes). This variable is zero for non-exporters.
*Avg Worker Type*: average worker fixed effect, estimated by the AKM decomposition, by firm.
*Notes*: Cross-sectional Regressions for firms with at least 4 workers, years 1995-2007. Different specifications in the columns. Standard errors, clustered at the level of the firm, are reported in parenthesis. All specifications but the first include a quadratic in the number of sampled workers, to control for the precision of the left-hand side variable.

# A Appendix

## A.1 Numerical simulation

[TO BE ADDED]

## A.2 Additional empirical results

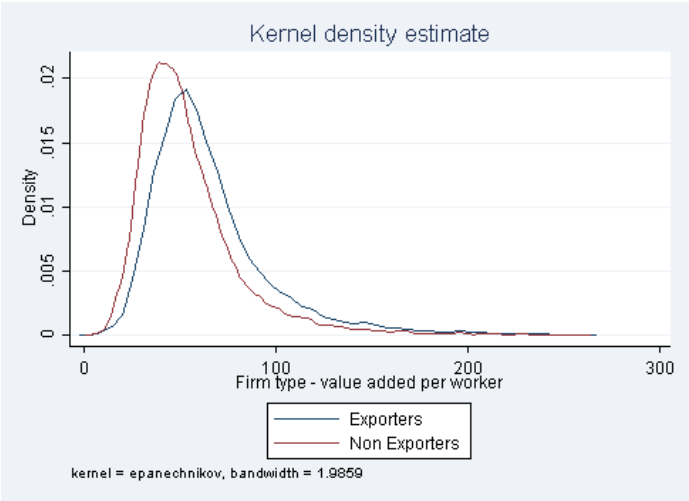


Figure A1: Distribution of Value Added per Worker in Exporting and Non-Exporting Firms

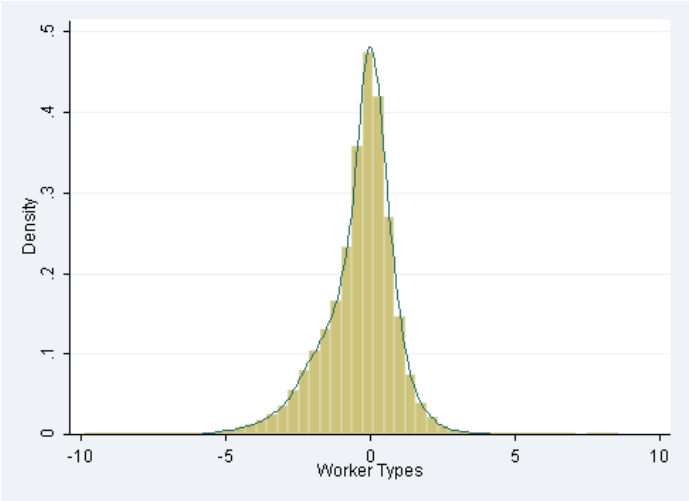


Figure A2: Distribution of Individual Effects, largest connected group

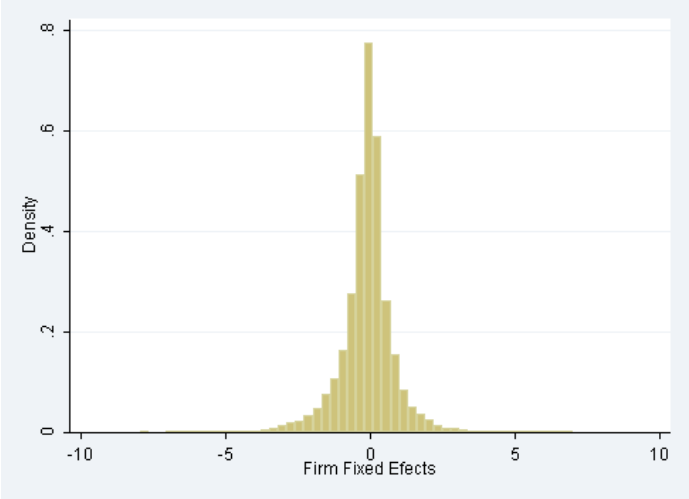


Figure A3: Distribution of Firm Effects, largest connected group

Table A1: *Summary Statistics*

| | Mean | Median | Std Deviation |
|---|---|---|---|
| Avg. Worker Type | -0.04 | -0.02 | 0.86 |
| Std Dev. Worker Fixed Effects | 0.62 | 0.52 | 0.41 |
| Std Dev. Worker Fixed Effects, White Collars | 0.55 | 0.47 | 0.36 |
| Std Dev. Worker Fixed Effects, Blue Collars | 0.50 | 0.36 | 0.41 |
| Std Dev. Worker Fixed Effects[a] | 0.62 | 0.52 | 0.41 |
| Std Dev. Worker Fixed Effects, White Collars[a] | 0.55 | 0.47 | 0.36 |
| Std Dev. Worker Fixed Effects, Blue Collars[a] | 0.50 | 0.36 | 0.41 |
| Num. Occupation | 4.90 | 4.00 | 2.44 |
| Domestic Market Share | 0.03 | 0.01 | 0.08 |
| Employment | 290.48 | 134.00 | 715.65 |
| Products | 8.57 | 9.01 | 4.22 |
| Share of Non Production Worker | 0.34 | 0.29 | 0.25 |
| Value Added per worker | 70.76 | 45.71 | 161.35 |

[a] Conditioning on a sample of firms with at least 4 sampled workers.

Table A2: *Summary Statistics: Market Access Shocks*

| | Mean | Median | Std Deviation |
|---|---|---|---|
| *Weighted Tariff* | 5.58 | 5.03 | 3.49 |
| *Market Access Shock*$_1$ | 12.93 | 14.32 | 6.15 |
| *Market Access Shock*$_2$ | 12.89 | 14.27 | 6.12 |

*Weighted Tariff*: Weighted average - across destination - of tariff levels in a given industry $i$ at time $t$, where weights are the share of world exports to that particular destination in that industry and year.
*Market Access Shock*$_1$: Weighted average - across destinations, excluding France - of the demand faced by a given industry $i$ at time $t$, where the weights are the share of world exports to that particular destination in that industry the previous year.
*Market Access Shock*$_2$: Weighted-average - across destinations - of the demand faced by a given industry $i$ at time $t$, where the weights are the share of world exports to that particular destination in that industry the previous year.

Table A3: Classification of CS Occupation into 'white' and 'blue' collar workers.

| CS code | White Collar Jobs |
|---|---|
| 3 | Executives and Higher Intellectual Professions |
| 31 | Health Professionals and Lawyers |
| 33 | Senior Official in Public Administration |
| 34 | Teachers, Scientific Professions |
| 35 | Information, arts and entertainment |
| 37 | Administrative and Commercial skilled workers |
| 38 | Engineers and technical managers |
| 4 | Intermediate Occupations |
| 42 | Teachers and related |
| 43 | Intermediate occupations, health and social work |
| 44 | Religious |
| 45 | Intermediate administrative professions in Public Administration |
| 46 | Intermediate administrative and commercial occupation in Enterprises |
| 47 | Technicians |
| 48 | Foremen, supervisors |
| CS code | Blue Collar Jobs |
| 5 | Clericals |
| 52 | Civilian Employees and officers in Public Service |
| 53 | Protective Services |
| 54 | Administrative Employees |
| 55 | Commercial workers |
| 56 | Personal services workers |
| 6 | Labourers |
| 62 | Qualified Industrial Labourers |
| 63 | Qualified craft labourers |
| 64 | Drivers |
| 65 | Storage and Transport workers |
| 67 | Non-Qualified Industrial Labourers |
| 68 | Non-Qualified craft labourers |
| 69 | Farm Workers |

Table A4: Match Effect Regressions: *Average Worker Type*, more than 4 workers

| Variables | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Average Worker Type | | | | | |
| Export | $0.078^a$ | $0.050^b$ | $0.046^b$ | $0.050^b$ | $0.041^c$ | 0.029 |
| | (0.023) | (0.023) | (0.023) | (0.023) | (0.023) | (0.026) |
| N.Occ. | | $0.010^a$ | $0.014^a$ | $0.015^a$ | $0.008^b$ | -0.004 |
| | | (0.004) | (0.003) | (0.002) | (0.004) | (0.004) |
| log *empl* | | $0.022^b$ | | | $0.020^c$ | $0.032^a$ |
| | | (0.010) | | | (0.011) | (0.012) |
| log *VA per worker* | | | | $0.064^a$ | $0.063^a$ | 0.018 |
| | | | | (0.015) | (0.015) | (0.015) |
| log *dom.share* | | | $0.008^b$ | | 0.002 | 0.001 |
| | | | (0.004) | | (0.005) | (0.005) |
| log *N. Products* | | | | | | 0.003 |
| | | | | | | (0.006) |
| *white share* | | | | | | $0.415^a$ |
| | | | | | | (0.034) |
| Const. | $9.513^a$ | $9.239^a$ | $9.391^a$ | $9.251^a$ | $9.169^a$ | $9.210^a$ |
| | (0.571) | (0.523) | (0.513) | (0.489) | (0.509) | (0.580) |
| Sector-Year | y | y | y | y | y | y |
| Obs. | 68,219 | 68,219 | 68,219 | 68,219 | 68,219 | 68,219 |
| $R^2$ | 0.013 | 0.016 | 0.016 | 0.017 | 0.017 | 0.028 |

*N.Occ.*: number of occupations, based on 2 digit occupational codes for France.
log *empl.* log-employment.
log *VA per worker*: log-value added per worker.
log *dom.share*: log-domestic market share, at the 4 digit sector level.
*white share*: share of non-production worker.
log *N. Products*: log-number of exported products (HS6 codes). This variable is zero for non-exporters.
*Notes*: Cross-sectional Regressions for firms with at least 4 workers, years 1995-2007. Different specifications in the columns. Standard errors, clustered at the level of the firm, are reported in parenthesis. All specifications but the first include a quadratic in the number of sampled workers, to control for the precision of the left-hand side variable.

Table A5: Match Effect Regressions: *Standard Deviation of Worker Types*, firms with more than 4 workers

| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Standard Deviation of Worker Types, more than 4 workers | | | | | |
| Export | -0.016[c] | -0.014 | -0.031[a] | -0.045[a] | -0.020[b] | -0.032[a] |
| | (0.009) | (0.009) | (0.010) | (0.009) | (0.009) | (0.011) |
| Avg. Worker | -0.073[a] | -0.074[a] | -0.075[a] | -0.077[a] | -0.080[a] | -0.080[a] |
| | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) |
| N.Occ | | 0.042[a] | 0.021[a] | 0.017[a] | 0.040[a] | 0.036[a] |
| | | (0.002) | (0.001) | (0.001) | (0.002) | (0.002) |
| log *VA per worker* | | | | 0.054[a] | 0.053[a] | 0.035[a] |
| | | | | (0.006) | (0.006) | (0.006) |
| log *empl* | | -0.080[a] | | | -0.076[a] | -0.077[a] |
| | | (0.004) | | | (0.004) | (0.004) |
| log *dom.share* | | | -0.007[a] | | 0.0003 | -0.001 |
| | | | (0.002) | | (0.002) | (0.002) |
| *white share* | | | | | | 0.156[a] |
| | | | | | | (0.014) |
| log *N. Products* | | | | | | 0.004[c] |
| | | | | | | (0.0025) |
| Const. | 1.138[a] | 1.352[a] | 0.933[a] | 0.908[a] | 1.288[a] | 1.359[a] |
| | (0.112) | (0.050) | (0.052) | (0.047) | (0.060) | (0.057) |
| Sector-Year | y | y | y | y | y | y |
| Obs. | 62,296 | 62,296 | 62,296 | 62,296 | 62,296 | 62,296 |
| $R^2$ | 0.073 | 0.099 | 0.085 | 0.088 | 0.103 | 0.110 |

*N.Occ.*: number of occupations, based on 2 digit occupational codes for France.
log *empl.* log-employment.
log *VA per worker*: log-value added per worker.
log *dom.share*: log-domestic market share, at the 4 digit sector level.
*white share*: share of non-production worker.
log *N. Products*: log-number of exported products (HS6 codes). This variable is zero for non-exporters.
*Avg Worker Type*: average worker fixed effect, estimated by the AKM decomposition, by firm.
*Notes*: Cross-sectional Regressions for firms with at least 4 workers, years 1995-2007. Different specifications in the columns. Standard errors, clustered at the level of the firm, are reported in parenthesis. All specifications but the first include a quadratic in the number of sampled workers, to control for the precision of the left-hand side variable.

Table A6: Market Access Regressions: *Average*, at least 4 workers. Firm-level weights

| Variables | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Average of Workers' Fixed Effects, at least 4 workers | | | | | |
| Market Access*Export | 0.004[b] | 0.000 | 0.000 | 0.000 | -0.001 | -0.001 |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| Export | 0.030 | 0.036 | 0.029 | 0.036 | 0.031 | -0.032 |
| | (0.036) | (0.036) | (0.036) | (0.036) | (0.036) | (0.042) |
| N. Occ | | 0.017[a] | 0.022[a] | 0.024[a] | 0.015[a] | 0.002 |
| | | (0.005) | (0.004) | (0.004) | (0.005) | (0.005) |
| log *empl* | | 0.036[a] | | | 0.034[b] | 0.036[b] |
| | | (0.014) | | | (0.015) | (0.015) |
| log *dom.share* | | | 0.013[a] | | 0.006 | 0.005 |
| | | | (0.005) | | (0.005) | (0.005) |
| log *VA per worker* | | | | 0.068[a] | 0.066[a] | 0.013 |
| | | | | (0.018) | (0.018) | (0.018) |
| log *N. Products* | | | | | | 0.019[c] |
| | | | | | | (0.011) |
| *white share* | | | | | | 0.439[a] |
| | | | | | | (0.037) |
| Sector-Year | y | y | y | y | y | y |
| Observations | 45,463 | 45,463 | 45,463 | 45,463 | 45,463 | 45,463 |
| R-squared | 0.022 | 0.026 | 0.026 | 0.027 | 0.028 | 0.041 |

*N.Occ.*: number of occupations, based on 2 digit occupational codes for France.
log *empl.* log-employment.
log *VA per worker*: log-value added per worker.
log *dom.share*: log-domestic market share, at the 4 digit sector level.
*white share*: share of non-production worker.
log *N. Products*: log-number of exported products (HS6 codes). This variable is zero for non-exporters.
*Notes*: Cross-sectional Regressions for firms with at least 4 workers, years 1995-2007. Different specifications in the columns. Standard errors, clustered at the level of the firm, are reported in parenthesis. All specifications but the first include a quadratic in the number of sampled workers, to control for the precision of the left-hand side variable.

Table A7: Market Access Regressions: *Standard Deviation*, at least 4 workers. Firm-level weights

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Variables | Standard Deviation of Workers' Fixed Effects, at least 4 workers | | | | | |
| Market Access*Export | -0.002[b] | -0.002[c] | -0.003[a] | -0.004[a] | -0.002[b] | -0.002[b] |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Export | 0.044[a] | 0.049[a] | 0.049[a] | 0.046[a] | 0.047[a] | 0.038[b] |
| | (0.014) | (0.014) | (0.014) | (0.014) | (0.014) | (0.017) |
| N. Occ | | 0.033[a] | 0.016[a] | 0.014[a] | 0.032[a] | 0.029[a] |
| | | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| log *empl* | | -0.018[a] | | | -0.083[a] | -0.079[a] |
| | | (0.005) | | | (0.006) | (0.006) |
| log *dom.share* | | | -0.004[b] | | 0.003[c] | 0.004[c] |
| | | | (0.002) | | (0.002) | (0.002) |
| log *VA per worker* | | | | 0.035[a] | 0.028[a] | 0.016[b] |
| | | | | (0.007) | (0.007) | (0.008) |
| *white share* | | | | | | 0.151[a] |
| | | | | | | (0.016) |
| Avg Worker Type | | | | | | -0.081[a] |
| | | | | | | (0.005) |
| log *N. Products* | | | | | | 0.001 |
| | | | | | | (0.004) |
| Sector-Year | y | y | y | y | y | y |
| Observations | 45,463 | 45,463 | 45,463 | 45,463 | 45,463 | 45,463 |
| R-squared | 0.058 | 0.074 | 0.063 | 0.064 | 0.075 | 0.104 |

*N.Occ.*: number of occupations, based on 2 digit occupational codes for France.
log *empl.* log-employment.
log *VA per worker*: log-value added per worker.
log *dom.share*: log-domestic market share, at the 4 digit sector level.
*white share*: share of non-production worker.
log *N. Products*: log-number of exported products (HS6 codes). This variable is zero for non-exporters.
*Avg Worker Type*: average worker fixed effect, estimated by the AKM decomposition, by firm.
*Notes*: Cross-sectional Regressions for firms with at least 4 workers, years 1995-2007. Different specifications in the columns. Standard errors, clustered at the level of the firm, are reported in parenthesis. All specifications but the first include a quadratic in the number of sampled workers, to control for the precision of the left-hand side variable.