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

Matilde Bombardini (University of British Columbia, CIFAR and NBER),
Gianluca Orefice (CEPII),
and Maria D. Tito (Federal Reserve Board)

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Abstract

This paper documents a novel fact about the hiring decisions of exporting firms versus non-exporting firms in a French matched employer-employee dataset. We construct the type of each worker using both a traditional wage regression and a theory-based approach and compute measures of the average worker type and worker type dispersion at the firm level. We find that exporting firms feature a lower type dispersion in the pool of workers they hire. This effect is quantitatively larger than the common finding in the literature that exporters pay higher wages because, among other factors, they employ better workers. The matching between exporting firms and workers is even tighter in sectors characterized by better exporting opportunities as measured by foreign demand or tariff shocks. Our findings are consistent with a model of matching between heterogeneous workers and firms in which 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, matching with the right worker becomes particularly important because deviations from the ideal match quickly reduce the higher potential value of the relationship. Hence, exporting firms select sets of workers that are less dispersed relative to the average. This analysis is suggestive of the presence of additional gains from trade due to improved sorting.

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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 and Shubik (1971) and Becker (1973). From those contributions we know that when firms and workers are complementary in production, then the allocation of high-type workers to high-type firms maximizes output. The second implication has received attention more recently by Card et al. (2013), who show that sorting of good workers to good firms can explain 35% of the recent increase in wage inequality in West Germany. The logic is that 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 (as in Kremer and Maskin, 1996).

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 the matching between firms and workers? When firms gain access to the foreign market, their revenue potential increases. When potential surplus is high, complementarity implies that 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 a higher average type and a lower type dispersion than non-exporting firms. While the first effect is predicted by other models (Helpman et al., 2010 and Sampson, 2014), 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 and 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, according to our results, quantitatively as strong as the effect of exporting on worker average type. While at an exporting firm worker ability is higher by 3% of a standard deviation, variability is lower by 4.9% of a standard deviation.

Obviously, the simple cross-sectional correlation between export status and type dispersion may be spuriously determined by omitted variables. Therefore, we adopt two empirical strategies in addition to our baseline estimation. The first is to show that the effect of exporting on type dispersion is stronger when exporters face a positive demand shock in foreign markets. In particular, we build measures of exporting opportunities in different sectors using tariffs and aggregate imports from the various countries to which France exports. Whether we build these measures at the firm or 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. The second approach in dealing with the correlation of export status with other unobserved characteristics (that may affect the choice of workers) is to employ instrumental variables. We again build a variable that interacts the firm export share to a given market in the previous period with changes in tariffs imposed by that country in that sector. Our instrument is valid according to standard criteria and qualitatively confirms our OLS results.

Our results are consistent with a simple open-economy extension of the model proposed by Eeckhout and Kircher (2011) and the implied variability in the worker type tolerated by the firm in their framework. On the one hand, because of complementarity, matching with a worker with ability below the firm's ideal type is associated with lower output; the difference from the optimal output tends to be larger the higher the firm productivity. On the other hand, a worker type that is above the optimal one for the firm 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, or that have access to the export market, tolerate less relative dispersion from their ideal worker type. If we interpret a firm as a collection of independent worker-job matches, this result translates to a lower variation in the ability of workers employed at exporting firms.

We consider alternative interpretations of our empirical result, based on changes in organizational structure that could also result from increased market access as in Caliendo and Rossi-Hansberg (2012) and Friedrich (2018). These studies find that firms respond to a positive trade shock, like increased market access, by adding hierarchical layers to their organization, thus inducing an increase in wage inequality within the firm. This effect on hierarchies is compatible with the mechanism linking type dispersion to export opportunities that we focus on. Nevertheless, the findings of Caliendo and Rossi-Hansberg (2012) and Friedrich (2018) suggest that we need to carefully control for occupational structure. We do this in two ways. First, we focus on type dispersion *within* occupation groups. Second, we control for a variable that captures changes in wage dispersion that are due to differences in the occupation structure of firms. Both results reassure us that these two mechanisms can be present in the data, but that our findings are not due to a hierarchical change in the firm due to export opportunities.

1.1 Literature Review

This paper contributes to the growing literature on international trade with heterogeneous workers and firms, which is surveyed in a recent chapter by Davidson and 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, and the process' implication for wage inequality. Three prominent examples are Sampson (2014), Helpman et al. (2010) and Helpman et al. (2017). The paper relates to a larger literature on the impact of trade on inequality, of which recent prominent examples are Feenstra and Hanson (1999), Costinot and Vogel (2010), Bustos (2012), Amiti and Cameron (2012), Verhoogen (2008), Krishna et al. (2014), Frías et al. (2009) and Frías et al. (2012).

The most closely related papers are Davidson et al. (2014) and Helpman et al. (2010) . While we discuss the latter in detail in Section 2 , it is constructive to understand the relation of our work to Davidson et al. (2014). That paper 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). Relative to Davidson et al. (2014), our approach shifts the focus to 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 and Kircher (2011) prove that firms' fixed effect deriving from a wage regression à la AKM might be negatively or not correlated with the true firm type, we are careful to avoid using those fixed effects as proxies for the firm type. We use instead variables constructed from firm-level data, such as sales, value added, and total employment.

The remainder of the paper is divided into three sections. Section 2 describes a theoretical framework that justifies our empirical investigation. Section 3 presents the estimation of worker types and the empirical results linking export status and dispersion of worker type in the firm. Section 4 concludes.

2 Theoretical Framework

The role of this section is to lay out a theoretical mechanism that explains 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, most importantly, the variation in worker type at the firm level. It is important to point out from the outset that we view the model as a stylized setting that illustrates some plausible forces that may explain our empirical results.

In the online appendix, we adapt the setup in Eeckhout and Kircher (2011) to a monopolistic competition model with a continuum of heterogeneous agents. Production occurs if matches are formed between firms and workers; we analyze the matching problem between one firm and one worker, and we interpret a firm with n workers as a solution to n independent problems.[1] Individual agents do not create output when unmatched, and, at each point in time, agents are either matched or unmatched. In the presence of complementarities in production and no frictions, we would observe perfect positive assortative matching, with every type of firm 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, as in Sampson (2014).

Here we are interested in analyzing the variation between workers employed by the same firm so we adopt the framework of Eeckhout and Kircher (2011), which in turn introduces constant search frictions as in Chade (2001) and Atakan (2006). Agent types are not observable before a meeting occurs and meetings occur at random. After meeting, workers and firms perfectly observe one another's type and decide whether to produce. The worker and the firm accept to match if the

[1] While the revenue function is concave in our original specification, a linearized version, following on the strategy proposed by Nocke and Yeaple (2014) and Fajgelbaum (2013), would simplify our results and guarantee that the solution to the matching problem between one firm and one worker extends to the case with n workers, where each match is an independent problem.

surplus from the relationship is non-negative: if both agents agree to match, they leave the market and split the surplus they generated according to Nash Bargaining; if unmatched, each agent pays a fixed cost to search in the second period. To simplify the analysis, Eeckhout and Kircher (2011) assume that the second period features perfect assortative matching. [2]

We adapt the model in Eeckhout and Kircher (2011) to an open economy, introducing, for some firms, the opportunity to export to a foreign market. This is a stylized way of introducing heterogeneous fixed costs of exporting, so that exporting and productivity are not perfectly correlated.[3] Additional revenues induce firms to become more selective when choosing the partners to match with. The benefits of additional revenues due to exporting are fully achieved only when matching with the ideal partner: since deviations from the ideal match quickly reduce the value of the relationship, matching with the right worker becomes particularly important. As a result, ceteris paribus, an exporter chooses a tighter matching set, normalized by its average worker ability, compared to a non-exporting firm. The mechanism we have described does not exclusively apply to exporting, but to any positive revenue shock. Nevertheless, the availability of data on exports and tariffs provides a fitting tool for identification. To summarize, we will take to the data the following two conjectures based on this theoretical framework:

Conjecture 1 *The set of workers employed by an exporting firm features higher average ability.*

Conjecture 2 *The set of workers employed by an exporting firm features lower ability dispersion, normalized by the average worker ability in the firm.*

The framework in Eeckhout and Kircher (2011) however, is not able to accommodate the endogenous choice of firm size; in the empirical section, we will be treating a firm with n workers as

[2] Eeckhout and Kircher (2011), Chade (2001) and Atakan (2006) share the features of a constant search cost and transferable utility. Eeckhout and Kircher (2011) adopt a simplified two-period model, while Chade (2001) and Atakan (2006) feature an infinite horizon setup.

[3] See Helpman et al. (2017) for a similar assumption.

a solution to n independent matching problems. Models, such as Eeckhout and Kircher (2016) or Grossman et al. (2017), endogenize the choice of firm size in a frictionless setting with heterogeneous workers and firms. In their frameworks, however, each firm hires only one type of worker, so their model cannot be employed to analyze within-firm type variation. At first, it may seem that the model in Helpman et al. (2010) and Helpman et al. (2017) could be applied to our setting, since it also describes the matching of heterogeneous firms and workers in the presence of search frictions and it features endogenous firm size. However there are two differentially important reasons why their model may not be entirely applicable in our setting. First, under the assumption of a Pareto distribution, exporters choose a higher cut-off for hiring workers and this implies that the ability distribution of workers within firm has higher standard deviation, higher mean, and a constant coefficient of variation. While this last prediction is not in line with out findings, it would be possible in principle to explore whether other distributions could deliver the result. However, 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; they experience a productivity draw that is only firm-specific. Their model describes a static equilibrium: If workers were to learn their true type, mismatched workers would move to firms where they could receive higher wages. Our estimation procedure, which presumes the existence of a fixed worker type, would be at odds with their view of ex-ante identical workers. In sum, we are not aware of a model that provides a solution to a dynamic matching problem between a firm and n workers and that features a non-degenerate distribution of worker types within a firm.

3 Empirical Analysis

Our empirical analysis proceeds in two steps. First we construct two proxies of worker type, both of which find a theoretical foundation in Eeckhout and Kircher (2011). The first proxy for worker type is the average wage of the worker over her job spells. The second proxy is a worker fixed effect from a wage regression, a methodology pioneered by Abowd et al. (1999) (AKM) and recently enriched by Card et al. (2013). In view of our adoption of the Eeckhout and Kircher (2011) framework, relying on fixed effects from a wage regression requires a discussion. It is important to remember that Eeckhout and Kircher (2011) show that the theoretically derived *firm* fixed effect is unrelated to the true firm type (because of the non-monotonicity of the wage in firm type). In the online appendix B.4 we adopt two methodologies to illustrate how instead the worker fixed effect maintains a monotonic relationship to the true worker type even if the firm fixed effect is uninformative. Obviously, we are then careful to separately construct measures of firm type that are not derived as firm fixed effects. In a second step, we propose various measures that approximate the matching set 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 detail, 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 Data

The data for our project come from three main sources: the Déclaration Annuelle des Données Sociales (DADS), the Enquête Annuelle d'Entreprises (EAE), and the French Customs Data.[4]

DADS is an administrative database of matched employer-employee information collected by the INSEE (Institut National de la Statistique et des Études É conomique). 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 wage-paying firms and legal entities established in France are required

[4]These data are subject to statistical secrecy and have been accessed at CEPII.

to file payroll declarations; only individual employers 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 enterprises born in the month of October of even-numbered years until 2001 and every year after that.[5] This choice is motivated by the need to follow workers across years and job positions in order to recover their type (see subsection 3.3).

Our extract stretches from 1995 to 2007. The initial data set contains around 24 million observations (corresponding to the triplet worker-firm-year) that 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,[6] 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% have more than one employer in a given year; for those, we selected the enterprise at which the individual worked the greatest 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 a predicted wage, based on a linear model including gender, an Île-de-France dummy, and in-firm experience. We obtain a final sample of $2,579,414$.

Following Eeckhout and Kircher (2011)'s insight, we have to find an alternative proxy for the type of firm to the standard estimated firm fixed effects. So we enrich the available set of firm-level

[5] 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.

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

variables by merging DADS with the Enquête Annuelle d'Entreprise (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 EAE, we collect information on sales (domestic and exports), total employment, value added, and the main sector of the firm (NAF700 4-digit classification).[7] 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 our empirical strategy.

Export-related information on French firms comes from the French Customs. The customs data include export records at the firm-product-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.

3.2 Institutional Background

It is important to discuss whether the features of the French institutional setting are a reasonable counterpart to the assumptions made in the theoretical framework. In particular, our framework relies on the assumption that wages are the outcome of a bargaining game between firms and

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

workers. This condition is key to the empirical analysis in order for wage outcomes to reflect workers' and firms' characteristics. The question is whether the institutional restrictions leave enough room for wages to vary within firm and potentially within occupation.

Since 1950, wage-setting institutions in France are organized according to a hierarchical principle. Wages are bargained at three different levels: (i) at the national level, a binding minimum wage (called Salaire Minimum Interprofessionnel de Croissance, SMIC) is set by the government;[8] (ii) at the industry level, employers' organizations and unions negotiate pay scales; wages are, then, negotiated occupation by occupation; and (iii) at the firm level, employers and unions usually negotiate wage increases.

Typically, in the 1970s and 1980s collective agreements were negotiated within different sectors between unions and employer associations, then extended by the Ministry of Labor 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 30 years. Three channels have been used to promote firm-level agreements: (i) the obligation for firms to negotiate wages each year, (ii) more possibilities offered to firms to deviate from industry-level agreements (*escape clauses*), and (iii) fiscal incentives.[9] 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 (Robien's laws in 1996, the first Aubry's law in 1998, the second Aubry's law in 2000) allowed the application of escape clauses to working hours' arrangements, reinforcing the trend toward decentralization. Escape

[8] 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.

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

clauses on pay were introduced in 2004; their use, however, has remained rather limited.[10]

Since the 1980s, firm-level negotiations acquired progressively more importance. The ICTWSS survey for France reports that bargaining predominantly[11] alternates between sector and firm level since 1981. 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 (Carlier and Naboulet, 2007).[12]

Firm-level bargaining, however, does not guarantee that workers employed at a given firm within the same occupation earn different wages. To provide evidence on worker-firm bargaining, we analyze the variability of wages across workers within firm-occupation cells in figure B8 in the B.5 online appendix. Figure B8 compares the overall (demeaned) wage distribution to the occupation-firm demeaned wage distribution. Although firm and occupation characteristics account for a large part of the overall wage variation, substantial variability in wages can still be observed across workers employed in the same occupation at the same firm. Table A3 precisely quantifies the importance of firm characteristics and worker observables in a wage variance decomposition. We start with a Mincerian specification of log wages on occupation dummies, gender, in-firm tenure, and a time-varying firm component; we use the Mincerian estimates to decompose the total wage variance into the contribution of worker observables, a between-firm component, the covariance between worker observables and the firm effect, and a within-firm component. The within-firm component accounts for a larger share of wage variation than what is jointly explained by firm and worker characteristics. In fact, the within-firm component explains 52% of the overall wage inequality in 1995; the percentage rises to 57.7% in 2007. This evidence corroborates the idea that the outcome of firm-level bargaining is not a common wage for all workers employed at a given firm within the same occupation, but rather that there is large scope for individual worker variation.

[10]Source: Institutional Characteristics of Trade Unions, Wage Setting, State Intervention and Social Pacts, 1960-2011, ICTWSS).

[11]A level is characterized as *predominant* if it accounts for at least 2/3 of the total bargaining coverage rate.

[12]In 1992, 40% of the workforce was covered by some firm-level agreement. Source: Abowd et al. (2012); authors' calculation based on data from wage structure survey in 1992.

3.3 Constructing Worker Types

We propose two strategies to construct worker type, which we denote as θ. The first strategy employs the average log wage of the worker over the years in which she is present in our dataset. The second strategy adopts the methodology proposed by AKM of extracting the individual worker component from a log wage regression.

Worker Type Proxy: Average Lifetime Wage - θ^{LW}

Our first methodology adopts the theoretically grounded average wage, in logs, of the worker over all her job spells - hereafter, *average lifetime wage*- to proxy for the worker type. In fact, in our reference framework, the average lifetime wage is monotonically related to the worker type θ: a more productive worker makes larger contributions to revenues and expects to match with a better firm in the frictionless equilibrium, obtaining, on average, a higher wage.[13]

We adopt a second strategy, the AKM methodology, for comparability with the earlier literature, but also provide a theoretical investigation of its validity (see online appendix).

Worker Type Proxy: Worker Fixed Effects - θ^{AKM}

The AKM methodology aims at decomposing individual workers' wages into a firm component and a worker component.[14] The basic specification relates a measure of log compensation for worker i employed in firm j at time t to worker and firm effects:

$$\ln w_{it} = x_{it}'\beta + \theta_i^{AKM} + \psi_{J(i,t)} + \varepsilon_{it} \quad (1)$$

[13]In section B.3 in the online appendix, we formally show that the average lifetime wage is increasing in the worker type θ.

[14]The AKM methodology has seen a very large number of applications; among others, for example, Abowd et al. (2003), Abowd et al. (2006), Abowd et al. (2007), Abowd et al. (2008), Abowd, McKinney and Vilhuber (2009), Abowd, Haltiwanger and Lane (2009), Carneiro et al. (2012), and Torres et al. (2013).

where θ_i^{AKM} 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 θ_i^{AKM} captures persistent differences in compensation explained by ability and other time-invariant worker characteristics. We assume that the error term ε_{it} is i.i.d. across time and workers with mean zero. This assumption requires that employment mobility is exogenous, depending only on observable characteristics and on person and firm effects. More precisely, the fixed effects estimator conditions on the whole sequence of establishments at which each worker is observed; this implies that the exogenous mobility assumption is not violated in the presence of systematic mobility patterns driven by the person effect θ_i^{AKM} and/or the sequence of firm effects $\left(\psi_{J(i,t)}, \psi_{J(i,t+1)}, \ldots, \psi_{J(i,T)}\right)$. The assumption is, instead, violated if mobility depends, for example, on match-specific components of wages.[15] Following Card et al. (2013), we perform a diagnostic test on the interaction between wage changes and mobility patterns. Figure B9 in the online appendix reports wage changes associated with job transitions classified based on the quartile of the firm type - the average wages of co-workers - for the origin and destination workplace; year zero denotes the year in which the move occurs. We find little or no variation in wages before the job change; this outcome is to be expected if selection or transitory wage components do not affect mobility patterns. Workers moving towards the lowest quartiles of the firm productivity distribution tend to experience a small reduction in wages after their transition; the wage increase for workers moving towards the top of the productivity distribution is more marked. However, the worker movements remain quite symmetric if looking at the sign of wage changes for movers, as shown in table B3 in the online appendix. In the presence of systematic mobility patterns, we should expect all wage changes to be positive; in our data, only half of the movers (around 52%) experience an increase in wages.

[15] The results estimated under the assumption that the error term ε_{it} includes a match effect $\eta_{iJ(i,t)}$ and an idiosyncratic term as in Card et al. (2013) and Woodcock (2008) are qualitatively similar to those in tables 1 and 2. We report the results for the standard deviation across worker types in table B13 in the online appendix.

We follow AKM for the explicit specification of (1). Our dependent variable is the log of annualized real wages.[16] We include as time-varying controls a quartic in employer-specific experience,[17] time dummies, a dummy for workers residing in Île-de-France, and time-varying gender effects (exactly, the interactions of sex with all the other variables).

The panel version of DADS does not contain information on education. AKM obtain information on the highest degree attained from the permanent demographic sample (Échantillon 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.[18]

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 of the individual's job spells; similarly, a firm effect is common to all employees of the firm. Identifying both effects requires mobility of workers across firms.[19] 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 possible to identify all but one individual and one firm effects per group.

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

[17] 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.

[18] 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.

[19] 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.

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.

The estimation of the fixed effects is performed using the *Gauss-Seidel* algorithm, proposed by Guimaraes and Portugal (2010). This algorithm consists of solving the partitioned set of normal equations, associated to (1), starting with 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 the worker is 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; moreover, it does not force us to drop small firms due to the large number of firm effects to estimate.[20]

We recover estimates for the fixed effects for 406,404 individuals and 31,649 firms. In the online appendix, we include the distribution of the worker fixed effects (figure B6) and firm fixed effects (figure B7) for the largest connected group.

Average Worker Type and Variation of Worker Type at the Firm-Level

With estimates of worker types at hand, we now proceed to construct measures of the average worker type and dispersion of worker type at firm j. Specifically, we construct the variables *Av-*

[20]The number of firms' fixed effect is too large for the *felsdv* estimator, for example. 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.

$WorkerType_{jt}$ and $SdWorkerType_{jt}$ as

$$
\begin{aligned}
AvWorkerType_{jt} &= \frac{1}{n_{jt}} \sum_{i \in I_{jt}} \hat{\theta}_i \\
SdWorkerType_{jt} &= \frac{1}{n_{jt}} \sqrt{\sum_{i \in I_{jt}} \left(\hat{\theta}_i - AvWorkerType_{jt}\right)^2}
\end{aligned}
$$

where $\hat{\theta}$ denotes our proxy for worker type, which is either θ^{LW} or θ^{AKM} and I_{jt} and n_{jt} are, respectively, the set and the number of workers employed by firm j at time t.

We build these measures only for firms with more than 5 sampled workers.[21] The choice of the 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. We consider each employment relation to be 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 should converge to the true measure. Choosing a higher threshold does not affect the results. If including firms with fewer than 5 sampled workers, instead, the coefficients on our variables of interest are of the correct sign but in some specifications are not significant. In the appendix, we report the results from GLS regressions that include all firms.[22] As an alternative, we also run weighted regressions using the in-firm average worker experience as weights (tables A15 and A16), we construct firm-level measures with worker types weighted by the worker years of experience (table B10), and we extract the worker experience from the average lifetime wage before aggregating our

[21]In empirical simulations, the estimation error in determining the standard deviation declines substantially when the number of sampled workers increases from 2 to 5. As the number of sampled worker increases, the bias continues to decline; the reduction, however, tend to be smaller.

[22]See tables A13-A14; we report the GLS results when using workers fixed effects as proxy for worker type in the online appendix, tables B8 and B9.

proxies (tables B11 and B12), to downweight those workers that are present in the sample for fewer years. All the results are in line with those on the restricted sample of firms with more than 5 workers.

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 and Kircher (2011) show that the relationship between true firm type and firm fixed effect estimated from a AKM-style wage regression is theoretically ambiguous – i.e., it can be positive, negative, or zero, a point also contemporaneously made in Lopes de Melo (2016). Eeckhout and 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 rely on three proxies for firm type: 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, $DomShare_j$, 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).[23] 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.

We first confirm the hypothesis put forward by Eeckhout and Kircher (2011) and Lopes de Melo

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

(2016) regarding the ability of the AKM firm fixed effects to capture the firm type. Table A4 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 lifetime wage, $Avg\ \theta_j^{LW}$, or by the average AKM worker fixed effect, $Avg\ \theta_j^{AKM}$, over the sample period at firm j. The first striking fact is the negative and large correlation (-0.80) between average worker type and the AKM firm fixed effects ψ, 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 either measure for the average worker type at the firm level. The three proxies for firm type are in turn all positively correlated with one another, but display small and sometimes opposite correlations with the AKM fixed effect ψ. In particular $DomShare_j$ and $VApw_j$ have a positive correlation of 0.01 and of 0.001 with ψ, respectively, while and $\log Emp_j$ displays a negative correlation of -0.01. As an alternative, we also compute the rank correlation of deciles from the three measures of firm productivity (table B4) and worker type (table B5); we assigned each agent to a decile based on its type distribution and then calculated the Spearman correlations. Our result confirm that the agent rankings are significantly and positively correlated across the different measures of firm and worker types.

Table A5 shows that the correlation pattern from table A4 is not unique to a few sectors. In column 4, we report the correlation between $Avg\ \theta_j^{AKM}$ and ψ_j by two-digit sector, while column 6 displays the analogous correlation between $DomShare_j$ and $Avg\ \theta_j^{LW}$. While the first set of correlations is always negative and significant, the second set of correlations is positive and significant, except in one case where the correlation is positive, but not significant. The evidence presented in tables A4 and A5 is consistent with the hypothesis put forward by Eeckhout and Kircher (2011) that the AKM firm fixed effect may not be correlated with the true firm type, although it is still possible that, as in Abowd et al. (2004), there is truly negative assortative matching between workers and firms or that the negative result is purely due to the statistical bias arising from the short nature of the panel.

3.5 Empirical Specification 1: Export Status and Acceptance 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 (2014) and, under the interpretation of permanent worker heterogeneity, Helpman et al. (2010). We believe this is a novel method of corroborating such a 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.

The following specification investigates *Conjecture 1*:

$$AvWorkerType_{jt} = \beta_0 + \beta_1 Export_{jt} + \beta_2 \ Firm \ Type_{jt} + D_{st} + u_{jt} \tag{2}$$

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 also 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 change over time for a given worker.[24] We add the number of occupations, $N.occ_{jt}$, and the share of white collar workers,[25] *whiteshare*, to

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

[25] The blue vs white collar classification is based on occupational codes. We report the classification we adopt in table B1 in the online appendix.

specification (2). 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 worker type.

In addition, all specifications except the first include a quadratic in the number of sampled workers to control for the precision of our left-hand side estimates.[26] Finally, all specifications include sector-year dummies, D_{st}.

The novel contribution of this paper is the investigation that exporters match with workers that are characterized by lower *relative* dispersion of ability. The following specification investigates *Conjecture 2*:

$$SdWorkerType_{jt} = \beta_0' + \beta_1' Export_{jt} + \beta_2' Firm\ Type_{jt} + D_{st} + u_{jt}'. \tag{3}$$

In our theoretical framework, the prediction regarding the link between worker type dispersion and export status (and productivity) requires adopting a scale-free measure of dispersion, that is either expressed in percentage terms or relative to the average worker type. In this regard, with the fixed effects estimated from a log-linearized equation, types are already expressed in percentage differences from one another, implying that our resulting measure of dispersion satisfies the scale-free requirement. Moreover, controlling for the average worker type in our specification is an alternative method to characterize scale-free results in terms of dispersion; thus, we will also add the average worker type in the specification with all controls.[27]

Similarly to specification (2), we include the number of occupations, $N.occ_{jt}$, the share of white

[26] In unreported results, we simulated the model and verified that differences in the number of observations available for exporters and non-exporters do not produce differential biases that can justify the quantitative estimates we obtain. In other words, exporting firms do not have a large enough number of observations to mechanically induce differences in average worker type and standard deviation by the amount we observe.

[27] An alternative specification with a scale-free measure of dispersion relies on the coefficient of variation of worker types; all results are very similar if we adopt that specification.

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}.

Our specifications exploit the variation within sectors and across firms with different export status, conditional on the firm type and other observable characteristics. Although the theory suggests that the firms becoming exporters should also tend to select workers with lower ability dispersion, there is not enough variability in our sample to exclusively exploit this source of variation. Figure B10 in the online appendix shows the unconditional distribution of firms by number of years they operate in foreign markets. Around 13% of the total number of firms are exporting only one year; the percentage tends to decline if considering firms active abroad for a longer time span.[28] Table B2 in the online appendix looks further into the variability of export status by number of years of activity abroad. The second column of table B2 reports the average length of the non-exporting spells by category, while the last column shows the number of years a firm appears in the data. A firm that exports for 3 years, for example, tends to have a non-exporting spell of 1.4 years; however, those firms are present in the sample only for 4.89 years. Such a pattern, which is observed across all other categories, suggests that firms tend to switch their export status, on average, no more than once over the years they are in the sample. This is why we exploit the within-sector variability across exporting and non-exporting firms in our estimation.

Both specifications (2) and (3) are estimated by OLS and standard errors are clustered at the level of the firm.

[28]The share of firms rises at 13 years due to the truncation of our data, as the category of firms active for 13 years on the export market also includes firms that are active for a longer time period.

3.5.1 Rank Correlation by Export Status

We develop an alternative strategy to test the prediction that exporters select a set of workers characterized by a lower dispersion. We compare the rank correlation between the average worker type and the firm type among exporters to the rank correlation between the average worker type and the firm types among non-exporters. A lower dispersion among exporters implies tighter sorting and should be associated with a larger correlation. We construct the rank correlation separately for exporters and for non-exporters for each sector-year and we employ the following specification to test for the existence of systematic differences in the correlation by export status :

$$\text{Corr}\left(AvWorkerType_{jt}, FirmType_{jt}\right)_{st} = \beta_0'' + \beta_1'' Export_{st} + D_s + D_t + u_{st}'' \tag{4}$$

where $Export_{st} = 1$ if the correlation is constructed for the set of exporting firms in sector s at time t. In addition to sector and time dummies, we also include the average (log) employment and the average domestic market share of firms in the same sector-year-export status cell because those characteristics might differentially affect the matching patterns and be correlated with export status.

3.5.2 Results

The estimation results relative to specifications (2) and (3) are presented in tables 1 and 2. Column 1 of table 1 reports a positive and statistically significant relationship between export status and the average type of the worker employed by the firm (θ^{LW}). 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 the 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.

Table 2 reports the results of the estimation of specification (3) and has a similar structure to table 1. 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, employment, and value added per worker). The inclusion of all the control variables in column (6) does not alter the negative and significant coefficient on the export dummy.

It is important to quantify the effect at the core of this paper. Based on our preferred specification in table 2, column 6, where we include all controls, the expected difference in the dispersion of worker type between exporter and non-exporter firms is about 0.020 points (holding the other variables constant). Considering that the dependent variable has a standard deviation of 0.41, an exporter features worker variability that is lower by 4.9% standard deviations. The effect on the mean worker type can be calculated using the results from table 1 and is of the same order of magnitude, but a little smaller: an exporting firm displays an average worker type that is 3% standard deviations higher.[29]

In table A6, we report the results for the sample of newly hired workers. The export dummy is negative and significant for the sample of the newly hired. However, we do not obtain the same result when repeating the same exercise for the group of stayers (table B6). This finding is consistent with the presence of firing costs and other labor market protection measures that plausibly make the firing margin less flexible than the hiring one.

Tables 3 and 4 report estimates for the same specifications as in tables 1 and 2, but employ a

[29]This magnitude has been computed using export coefficient of table 1, column 6. The standard deviation of the average worker type is 0.81. See table A1 for summary statistics.

different proxy for the worker type, i.e. the worker fixed effect from an AKM regression (θ^{AKM}). Table 3 reports again a positive relationship between export status and average worker type; the coefficient on export status remains positive, but loses its significance when adding controls for firm type and the occupation structure. Table 4 confirms a negative relationship between the dispersion of worker type and export status. Controlling for the type of firm (by using employment, domestic market share, and value added per worker), the coefficient on export remains negative.

Tables A7 and A8 present a further robustness of the result to the definition of the dependent variable. In particular, we employ the interquartile and the 90-10 interdecile range of worker type at firm j.[30] It is easy to verify that all previously described patterns appear again in this table. Exporting firms choose a narrower range of worker types.

3.5.3 Endogeneity of Export Status

We have not discussed so far the potential endogeneity of export status and the bias resulting from unobserved firm characteristics that may affect the export status and the standard deviation of worker types simultaneously. To address this concern, we develop an instrumental variable strategy.[31] We instrument export status using a measure of tariff faced by an individual firm:

$$\text{Firm Tariff}_{jt} = \ln\left(1 + \sum_{sr} \tau_{srt} \frac{\text{Exports}_{jr,t-1}}{\text{Exports}_{j,t-1}}\right) \tag{5}$$

where τ_{srt} is the tariff faced by firms in sector s exporting to country r at time t; we aggregate across countries using as weights the share of exports to country r of firm j over the total exports of firm j at time $t-1$, $\frac{\text{Exports}_{jr,t-1}}{\text{Exports}_{j,t-1}}$. Then we take the inverse of the weighted average tariff faced

[30] We construct the interquartile range IQR $\mathit{WorkerType}_{jt} = \hat{\theta}^{j,75th} - \hat{\theta}^{j,25th}$; a similar definition applies to the 90-10 interdecile range.

[31] As an additional strategy to mitigate the endogeneity concerns, we use firm characteristics in the first year in which the firm appears in the sample, to proxy for firm types. The results, available upon request, are not statistically different from what is reported in table 2.

by firm j in order to have the instrumental variable positively correlated with the export status. In table B7, we show the first stage regression results. The coefficient on the instrumental variable is positive and strongly significant in all specifications. The power of the instrument, expressed by the F-statistics of the first stage, is also shown in table B7. Our F statistics are quite high, well above 10, a value below which weak instrument concerns arise. The validity of our instrument relies on the orthogonality between the standard deviation of worker types (i.e., lifetime wages and AKM decomposition fixed effects) and the interaction between country-sector specific tariffs (τ_{srt}) and the share of the firm's exports to country r at time $t-1$, $\frac{\text{Exports}_{jr,t-1}}{\text{Exports}_{j,t-1}}$. Tariffs faced in export markets are arguably orthogonal to firm specific composition of worker types. We try to attenuate concerns regarding the correlation of firm's export shares with worker composition of the firm by using the lag of export shares at $t-1$. However, as an additional robustness for our IV strategy, in equation (5) we use firm's export share also at $t-3$, $\frac{\text{Exports}_{jr,t-3}}{\text{Exports}_{j,t-3}}$ (see columns 4-6 in tables 5 and 6) and at $t = 1995$, $\frac{\text{Exports}_{jr,1995}}{\text{Exports}_{j,1995}}$, the initial year in our sample (see table A9).

Tables 5 and 6 report the second stage results. The coefficient on export status remains positive in table 5, negative and significant in all specifications of table 6 - independently of the number of (year) lags we use in building the instrument. In particular, the OLS regression estimates of β_1 seem to be biased towards zero; this finding is consistent with the idea that more productive firms possess a better technology to search for their workers. Commenting on the magnitudes, exporting firms tend to select a workforce that is 38.5% of a standard deviation (sd) less dispersed and has higher ability by 28.3% of a sd compared to a non-exporting firm.

3.5.4 Additional Robustness

Tables 7 and A10 isolate changes in organizational structure that could also result from shocks to export opportunities. Table 7 introduces the firm-level dispersion of wages predicted by the firm occupation composition,

$$\text{Occ Predicted SD}_{jt} = \left[\sum_o \frac{\sum_{i \in I_o} \left(\ln w_{oi} - \ln \bar{w}_o \right)^2}{n_o} \eta_{ojt} + \sum_o \left(\ln \bar{w}_o - \ln \bar{w} \right)^2 \eta_{ojt} \right]^{1/2}$$

where o indexes an occupation, I_o is the set of workers in occupation o, n_o is the number of workers in occupation o, and η_{ojt} is the share at firm j of workers in occupation o at time t. Occ Predicted SD_{jt} primarily captures changes in wage dispersion that are due to differences in the occupational structure across firms. Occ Predicted SD_{jt}, similarly to *N. Occ.*, our alternative control for the occupation composition, is positively correlated with our measure of dispersion, but does not affect the significance nor the magnitude of Export, which remains negative and not significantly different from what we report in table 6.

Table A10 presents the results for specification (3) with an alternative measure of dispersion, a weighted average of the standard deviation of ability among different groups of workers. In particular, we divide occupations into *managers*, *executives* (white collar occupations), and *blue collar* (as reported in table B1) and we construct average employment shares for those occupational groups within the firm over time. We then weigh the standard deviation of lifetime wages for each group by its average employment share to construct our new dependent variable. The coefficient on the export dummy remains negative and significant in all specifications; in most columns, the magnitude of the coefficient is not significantly different from what is reported in table 6. This suggests that our result is not due to compositional differences between exporters and non-exporters.

If firms that offshore production reduce the set of task and retain highest paying occupation, they could also display higher average wages and smaller dispersion of skills. To exclude that our results are driven by offshoring, we control for the share of imported inputs in tables A11 and A12. The coefficient on the export dummy remains consistent with our baseline results.

Finally, tables 8 and B14 explore the result for specification (4). Table 8 excludes all worker-firm pairs with less than 5 sampled workers. We find that, within sector-year cells, the rank correlation across exporters is significantly larger than that across non-exporters. In particular, using the coefficient from column (8), the rank correlation is 11 percent of a standard deviation higher at exporters relative to non-exporters. This result is robust to the addition of sector-level controls, such as the average employment or value added per worker (columns (2)-(4) and (6)-(8)) and to a GLS specification (table B14). This findings suggests that differences in dispersions might translate into higher rank correlation between average worker types and firm types for exporters compared to non-exporters, controlling for average size differences.

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 firm 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. 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:

$$
\begin{aligned}
AvWorkerType_{jt} &= \gamma_0 + \gamma_1 Mkt\ Access_{st} \times Export_{jt} + \gamma_2 Mkt\ Access_{st} \\
&\quad + \gamma_3 Export_{jt} + D_{st} + v_{jt}, && (6) \\
SdWorkerType_{jt} &= \gamma_0' + \gamma_1' Mkt\ Access_{st} \times Export_{jt} + \gamma_2' Mkt\ Access_{st} \\
&\quad + \gamma_3' Export_{jt} + D_{st} + v_{jt}' && (7)
\end{aligned}
$$

where

$$
\begin{aligned}
MktAccess_{st} &= \sum_r MktAccess_{srt} \times \frac{French\ exports_{sr,t-1}}{French\ exports_{s,t-1}}\ , && (8) \\
MktAccess_{srt} &= \begin{cases} Tariffs_{srt} \quad \text{or} \\ Imports_{srt} \quad \text{or} \\ \frac{Imports_{srt}}{Tariffs_{srt}} \end{cases} ,
\end{aligned}
$$

$Imports_{srt}$ is the total value of imports by country r from the rest of the world,[32] $Tariffs_{srt}$ 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 $French\ exports_{s,t-1}$).[33] 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 of 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 worker type and a 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 $\frac{Imports_{srt}}{Tariffs_{srt}}$.

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

[33] In additional robustness checks, we resort to 1995 export shares to construct our market access variables. The results, available upon requests, are qualitatively similar to those in tables 9-12.

Results

Tables 9 and 10 report estimates of the coefficients in specifications (6) and (7) 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 (8). We do not present results for the case in which total import demand is deflated by the tariff faced by French exporters because they are very similar. Table 9 reports results on the average worker type; our coefficient of interest is positive and significant on all specifications. However, if evaluated at the mean of the market access measured by $Imports_{srt}$, an exporter does not feature a higher average worker ability; only exporters in sectors with a degree of openness larger than the average will enjoy an effect on the average worker type.

In table 10, we find that the estimated coefficient γ_1' is negative and significant in all specifications, 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. The coefficient on export status is negative and significant in all specifications. If evaluated at the mean of the market access measured by $Imports_{srt}$, an exporter features worker variability that is lower by 3.4% of a sd than a non-exporter (which is in line with our previous quantifications).

Tables 11 and 12 report estimates of the coefficients from specifications (6) and (7) when market access for a firm in sector s is measured by the average tariff faced by exporters in sector s. Only columns 4-6 of table 11 report a negative coefficient γ_1 - which is line with the prediction - but not statistically significant.

Table 12 reports very similar results to table 10: better export market conditions as measured by a lower tariff faced on the export market result in a tighter matching set for exporting firms. So, contrary to table 11, the effect of export opportunities on the standard deviation of worker type seems more robust to the definition of market access. In particular, firms exporting in country-sector with *mean* market access (mean value equal to 5.58 in our sample) have a lower worker variability than non-exporters (13.7% standard deviation units), with such a gap increasing with the market access of the firm.

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 average type and lower type dispersion. This finding can be rationalized in a model of matching with search frictions in which more productive firms and exporting firms match with better workers and tolerate a lower degree of dispersion among the workers employed.

What are the implications of our results in terms of welfare? An open-economy Eeckhout and Kircher (2011) framework suggests the presence of 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, while the costs of mismatch decreases across exporters after a trade liberalization, the overall welfare result depends on which effect prevails. We leave this interesting, but non-trivial, evaluation of welfare effects to future research.

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Table 1: Pooled Cross-Section Regressions: *Average Worker Type*, more than 5 workers

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Worker Type: Average Lifetime Wage θ^{LW}					
Export	0.142^a	0.058^a	0.060^a	0.075^a	0.036^a	0.025^c
	(0.012)	(0.012)	(0.012)	(0.011)	(0.011)	(0.013)
N.Occ		0.017^a	0.033^a	0.034^a	0.013^a	-0.002
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
log empl		0.114^a			0.113^a	0.118^a
		(0.006)			(0.006)	(0.006)
log dom.share			0.025^a		0.004^b	0.0033^c
			(0.002)		(0.002)	(0.002)
log VA per worker				0.166^a	0.165^a	0.105^a
				(0.008)	(0.008)	(0.008)
white share						0.526^a
						(0.019)
log N. Products						0.006^c
						(0.003)
Sector-Year	y	y	y	y	y	y
Obs.	57,469	57,469	57,469	57,469	57,469	57,469
R^2	0.136	0.201	0.188	0.213	0.236	0.301

Export: dummy=1 if firm exports.
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.
[a] significant at 1%, [b] significant at 5%, [c] significant at 10%.
Notes: Cross-Sectional Regressions for firms with more than 5 workers, years 1995-2007. The dependent variable is the average lifetime wage of workers within a firm. Different specifications in the columns. Standard errors, clustered at the level of the firm, are reported in parentheses. 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 2: Pooled Cross-Section Regressions: *Standard Deviation of Worker Type*, more than 5 workers

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Worker Type: Average Lifetime Wage θ^{LW}					
Export	-0.035[a]	-0.017	-0.037[a]	-0.052[a]	-0.020[b]	-0.020[b]
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)
N.Occ		0.031[a]	0.013[a]	0.010[a]	0.030[a]	0.025[a]
		(0.002)	(0.002)	(0.001)	(0.002)	(0.001)
log empl		-0.107[a]			-0.108[a]	-0.022[a]
		(0.005)			(0.005)	(0.004)
log dom.share			-0.008[a]		0.001	0.002
			(0.002)		(0.002)	(0.001)
log VA per worker				0.045[a]	0.043[a]	0.108[a]
				(0.006)	(0.006)	(0.005)
white share						0.482[a]
						(0.013)
log N. Products						0.013[a]
						(0.002)
Avg Lifetime Wage						-0.730[a]
						(0.009)
Sector-Year	y	y	y	y	y	y
Obs.	57,469	57,469	57,469	57,469	57,469	57,469
R^2	0.062	0.089	0.067	0.068	0.092	0.542

Export: dummy=1 if firm exports.
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. Lifetime Wage: workers' lifetime wage, averaged by firm.
[a] significant at 1%, [b] significant at 5%, [c] significant at 10%.
Notes: Cross-Sectional Regressions for firms with more than 5 workers, years 1995-2007. The dependent variable is the dispersion across lifetime wages of workers within a firm. Different specifications in the columns. Standard errors, clustered at the level of the firm, are reported in parentheses. 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 3: Pooled Cross-sectional Regressions: *Average Worker Type*, more than 5 workers

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Worker Type: AKM worker fixed effect θ^{AKM}					
Export	0.079^a	0.030	0.036	0.039	0.025	0.013
	(0.027)	(0.028)	(0.028)	(0.027)	(0.028)	(0.031)
N.Occ.		0.014^a	0.022^a	0.022^a	0.012^a	0.001
		(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
log empl		0.053^a			0.055^a	0.059^a
		(0.013)			(0.014)	(0.014)
log dom.share			0.007^c		-0.002	-0.003
			(0.004)		(0.004)	(0.005)
log VA per worker				0.060^a	0.062^a	0.014
				(0.014)	(0.015)	(0.015)
white share						0.421^a
						(0.036)
log N. Products						0.007
						(0.009)
Sector-Year	y	y	y	y	y	y
Obs.	54,633	54,633	54,633	54,633	54,633	54,633
R^2	0.020	0.027	0.026	0.027	0.028	0.040

Export: dummy=1 if firm exports.
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. Lifetime Wage: workers' lifetime wage, averaged by firm.
^{a} significant at 1%, ^{b} significant at 5%, ^{c} significant at 10%.
Notes: Cross-sectional Regressions for firms with more than 5 workers, years 1995-2007. The dependent variable is the within-firm average across worker fixed effects extracted from an AKM regression that includes a quartic in employer-specific experience, time-dummies, a dummy for workers residing in Île-de-France, and time-varying gender effects. Different specifications in the columns. Standard errors, clustered at the level of the firm, are reported in parentheses. 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 of Worker Type*, more than 5 workers

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Worker Type: AKM worker fixed effect θ^{AKM}					
Export	-0.036[a]	-0.020[c]	-0.039[a]	-0.052[a]	-0.029[b]	-0.042[a]
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.013)
N.Occ.		0.029[a]	0.013[a]	0.010[a]	0.028[a]	0.025[a]
		(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
log empl		-0.096[a]			-0.096[a]	-0.092[a]
		(0.005)			(0.006)	(0.006)
log dom.share			-0.007[a]		0.0004	-0.001
			(0.002)		(0.002)	(0.002)
log VA per worker				0.036[a]	0.035[a]	0.024[a]
				(0.007)	(0.007)	(0.007)
white share						0.130[a]
						(0.016)
log N. Products						0.010[a]
						(0.003)
Avg Worker Type						-0.086[a]
						(0.005)
Sector-Year	y	y	y	y	y	y
Obs.	54,633	54,633	54,633	54,633	54,633	54,633
R^2	0.065	0.087	0.069	0.070	0.088	0.120

Export: dummy=1 if firm exports.
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. Lifetime Wage: workers' lifetime wage, averaged by firm.
Avg Worker Type: average worker fixed effect, estimated by the AKM decomposition, by firm.
[a] significant at 1%, [b] significant at 5%, [c] significant at 10%.
Notes: Cross-sectional Regressions for firms with more than 5 workers, years 1995-2007. The dependent variable is the within-firm dispersion across worker fixed effects extracted from an AKM regression that includes a quartic in employer-specific experience, time-dummies, a dummy for workers residing in Île-de-France, and time-varying gender effects. Different specifications in the columns. Standard errors, clustered at the level of the firm, are reported in parentheses. 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: IV Regressions: *Average Worker Type*, more than 5 workers

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Worker Type: Average Lifetime Wage θ^{LW}					
	Exp Share_{t-1}			Exp Share_{t-3}		
Export	0.195[a]	0.047	0.146[b]	0.229[a]	0.059[b]	0.229[a]
	(0.027)	(0.030)	(0.065)	(0.026)	(0.030)	(0.073)
N.Occ.		0.007[b]	-0.002		0.007[b]	-0.002
		(0.003)	(0.003)		(0.004)	(0.004)
log empl		0.137[a]	0.140[a]		0.139[a]	0.144[a]
		(0.011)	(0.010)		(0.012)	(0.011)
log dom.shared		0.006	0.005		0.006	0.004
		(0.004)	(0.003)		(0.004)	(0.004)
log VA per worker		0.185[a]	0.117[a]		0.188[a]	0.123[a]
		(0.013)	(0.013)		(0.014)	(0.014)
white share			0.566[a]			0.571[a]
			(0.030)			(0.031)
log N. Products			-0.033[b]			-0.051[a]
			(0.016)			(0.018)
Sector-Year	y	y	y	y	y	y
Obs.	16,072	16,072	16,072	13,217	13,217	13,217
R^2	0.183	0.286	0.354	0.186	0.286	0.351

Export: dummy=1 if firm exports.
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.
[a] significant at 1%, [b] significant at 5%, [c] significant at 10%.
Notes: IV Regressions for firms with more than 5 workers, years 1995-2007. The dependent variable is the average lifetime wage of workers within a firm. Export status is instrumented using tariffs and the previous year export share in columns (1)-(3); columns (4)-(6) use the $t-3$ export share. Standard errors, clustered at the level of the firm, are reported in parentheses. 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: IV Regressions: *Standard Deviation of Worker Type*, more than 5 workers

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Worker Type: Average Lifetime Wage θ^{LW}					
	Exp Share$_{t-1}$			Exp Share$_{t-3}$		
Export	-0.075^a	-0.081^a	-0.153^a	-0.085^a	-0.093^a	-0.158^a
	(0.019)	(0.029)	(0.035)	(0.023)	(0.027)	(0.058)
N.Occ.		0.013^a	0.027^a		0.029^a	0.022^a
		(0.002)	(0.003)		(0.003)	(0.002)
log empl		-0.093^a	-0.013^a		-0.101^a	-0.014^c
		(0.009)	(0.005)		(0.011)	(0.008)
log dom.share		0.009^a	0.010^a		0.010^a	0.010^a
		(0.001)	(0.001)		(0.003)	(0.002)
log VA per worker		0.031^a	0.101^a		0.022^b	0.096^a
		(0.010)	(0.005)		(0.0105)	(0.009)
white share			0.465^a			0.450^a
			(0.015)			(0.021)
log N. Products			0.045^a			0.045^a
			(0.015)			(0.014)
Avg. Lifetime Wage			-0.733^a			-0.726^a
			(0.012)			(0.015)
Sector-Year	y	y	y	y	y	y
Obs.	16,072	16,072	16,072	13,217	13,217	13,217
R^2	0.058	0.064	0.544	0.055	0.079	0.54

Export: dummy=1 if firm exports.
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. Lifetime Wage: workers' lifetime wage, averaged by firm.
^{a} significant at 1%, ^{b} significant at 5%, ^{c} significant at 10%.
Notes: IV Regressions for firms with more than 5 workers, years 1995-2007. The dependent variable is the dispersion across lifetime wages of workers within a firm. Export status is instrumented using tariffs and the previous year export share in columns (1)-(3); columns (4)-(6) use the $t-3$ export share. Standard errors, clustered at the level of the firm, are reported in parentheses. 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: IV Regressions: *Standard Deviation of Worker Type.*
Occupation Predicted Std Dev, more than 5 workers

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Worker Type: Average Lifetime Wage θ^{LW}					
	Exp Share$_{t-1}$			Exp Share$_{t-3}$		
Export	-0.084^a	-0.069^b	-0.151^a	-0.097^a	-0.081^a	-0.155^a
	(0.024)	(0.028)	(0.049)	(0.023)	(0.027)	(0.057)
Occ Predicted SD	0.028^a	0.135^a	0.035^a	0.027	0.133^a	0.031^a
	(0.014)	(0.006)	(0.006)	(0.015)	(0.007)	(0.007)
N.Occ.		0.049^a	0.026^a		0.049^a	0.027^a
		(0.003)	(0.002)		(0.004)	(0.003)
log empl		-0.167^a	-0.032^a		-0.166^a	-0.030^a
		(0.011)	(0.008)		(0.012)	(0.008)
log dom.share		0.009^a	0.010^a		0.009^a	0.010^a
		(0.003)	(0.002)		(0.003)	(0.002)
log VA per worker		0.026^a	0.098^a		0.018^c	0.093^a
		(0.009)	(0.008)		(0.010)	(0.009)
white share			0.464^a			0.450^a
			(0.019)			(0.021)
log N. Products			0.045^a			0.045^a
			(0.012)			(0.014)
Avg. Lifetime Wage			-0.722^a			-0.717^a
			(0.014)			(0.015)
Sector-Year	y	y	y	y	y	y
Obs.	16,072	16,072	16,072	13,217	13,217	13,217
R^2	0.065	0.117	0.546	0.061	0.112	0.544

Export: dummy=1 if firm exports.
Occ Predicted SD: firm-level dispersion of wages predicted by the firm occupation composition.
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. Lifetime Wage: workers' lifetime wage, averaged by firm.
^{a} significant at 1%, ^{b} significant at 5%, ^{c} significant at 10%.
Notes: IV Regressions for firms with more than 5 workers, years 1995-2007. The dependent variable is the dispersion across lifetime wages of workers within a firm. Export status is instrumented using tariffs and the previous year export share in columns (1)-(3); columns (4)-(6) use the $t-3$ export share. Standard errors, clustered at the level of the firm, are reported in parentheses. 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: Sectoral Rank Correlations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables				Rank Correlation				
Export	0.042^a	0.029^a	0.023^b	0.017^c	0.042^a	0.037^a	0.026^a	0.027^c
	(0.008)	(0.010)	(0.010)	(0.010)	(0.008)	(0.014)	(0.010)	(0.014)
log empl		0.009^c		0.004		0.003		-0.001
		(0.005)		(0.005)		(0.009)		(0.009)
log VA per worker			0.077^a	0.075^a			0.064^a	0.064^a
			(0.017)	(0.017)			(0.023)	(0.024)
Sector,Year	y[1]	y[1]	y[1]	y[1]	y[2]	y[2]	y[2]	y[2]
Obs.	3,836	3,836	3,836	3,836	3,836	3,836	3,836	3,836
R^2	0.041	0.042	0.049	0.049	0.195	0.195	0.198	0.198

[1] 2-digit sector dummies.
[2] 4-digit sector dummies.
log empl: average log-employment.
log VA per worker: average log-value added per worker.
[a] significant at 1%, [b] significant at 5%, [c] significant at 10%.
Notes: Industry regressions, years 1995-2007. We exclude all firm-worker pairs with less than 5 sampled workers. Standard errors, clustered at the sector-level, are reported in parentheses.

Table 9: Market Access Regressions: *Average Worke Type*, more than 5 workers

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Worker Type: Average Lifetime Wage θ^{LW}					
Market Access*Export	0.014^a	0.012^a	0.011^a	0.012^a	0.013^a	0.013^a
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Market Access	-0.016^a	-0.014^a	-0.013^a	-0.012^a	-0.015^a	-0.018^a
	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.003)
Export	-0.052	-0.078	-0.106^b	-0.114^b	-0.108^b	-0.168^a
	(0.051)	(0.050)	(0.047)	(0.050)	(0.050)	(0.050)
N.Occ.		0.039^a	0.015^a	0.032^a	0.035^a	-0.002
		(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
log empl			0.125^a			0.125^a
			(0.005)			(0.005)
log dom.share				0.031^a		0.004^b
				(0.002)		(0.002)
log VA per worker					0.158^a	0.096^a
					(0.008)	(0.006)
white share						0.500^a
						(0.024)
log N. Products						0.008^b
						(0.003)
Sector[1]-Year	y	y	y	y	y	y
Observations	44,728	44,728	44,728	44,728	44,728	44,728
R-squared	0.142	0.184	0.209	0.196	0.215	0.299

[1] 2-digit sector dummies.
Export: dummy=1 if firm exports.
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. Lifetime Wage: workers' lifetime wage, averaged by firm.
Market Access: weighted-average - across destinations - of the demand faced by a given industry i (4 digit sector) at time t, where the weights are the share of world exports to that particular destination in that industry the previous year.
^{a} significant at 1%, ^{b} significant at 5%, ^{c} significant at 10%.
Notes: Cross-sectional Regressions for firms with more than 5 workers, years 1995-2007. The dependent variable is the average lifetime wage of workers within a firm. Different specifications in the columns. Standard errors, clustered at the level of the firm, are reported in parentheses. 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: Market Access Regressions: *Standard Deviation of Worker Type*, more than 5 workers

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Worker Type: Average Lifetime Wage θ^{LW}					
Market Access*Export	-0.009[a]	-0.009[a]	-0.009[a]	-0.009[a]	-0.009[a]	-0.009[a]
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Market Access	0.011[a]	0.012[a]	0.011[a]	0.011[a]	0.012[a]	0.011[a]
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Export	0.096[b]	0.089[c]	0.113[b]	0.096[b]	0.080[c]	0.094[b]
	(0.048)	(0.047)	(0.046)	(0.048)	(0.046)	(0.041)
N.Occ.		0.011[a]	0.031[a]	0.012[a]	0.010[a]	0.026[a]
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
log empl			-0.107[a]			-0.105[a]
			(0.004)			(0.004)
log dom.share				-0.006[a]		0.002
				(0.002)		(0.002)
log VA per worker					0.050[a]	0.033[a]
					(0.006)	(0.005)
white share						0.158[a]
						(0.018)
Avg Lifetime Wage						-0.104[a]
						(0.004)
log N. Products						0.009[a]
						(0.003)
Sector[1]-Year	y	y	y	y	y	y
Obs.	44,728	44,728	44,728	44,728	44,728	44,552
R^2	0.068	0.071	0.094	0.072	0.075	0.143

[1] 2-digit sector dummies.
Export: dummy=1 if firm exports.
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. Lifetime Wage: workers' lifetime wage, averaged by firm.
Market Access: weighted-average - across destinations - of the demand faced by a given industry i (4 digit sector) at time t, where the weights are the share of world exports to that particular destination in that industry the previous year.
[a] significant at 1%, [b] significant at 5%, [c] significant at 10%.
Notes: Cross-sectional Regressions for firms with more than 5 workers, years 1995-2007. The dependent variable is the dispersion across lifetime wages of workers within a firm. Different specifications in the columns. Standard errors, clustered at the level of the firm, are reported in parentheses. 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: Tariff Regressions: *Average Worker Type*, more than 5 workers

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Worker Type: Average Lifetime Wage θ^{LW}					
Weighted Tariff*Export	0.002	0.001	0.001	-0.001	-0.001	-0.004
	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Weighted Tariff	0.001	0.002	0.002	0.00395	0.006^c	0.012^a
	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Export	0.128^a	0.082^a	0.045^b	0.050^b	0.071^a	0.039^c
	(0.023)	(0.021)	(0.020)	(0.020)	(0.021)	(0.021)
N.Occ.		0.039^a	0.016^a	0.033^a	0.035^a	-0.002
		(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
log empl			0.123^a			0.124^a
			(0.005)			(0.005)
log dom.share				0.031^a		0.005^a
				(0.002)		(0.002)
log VA per worker					0.161^a	0.099^a
					(0.008)	(0.007)
white share						0.512^a
						(0.021)
log N. Products						0.004
						(0.003)
Sector[1]-Year	y	y	y	y	y	y
Obs.	48,280	48,280	48,280	48,280	48,280	48,280
R^2	0.143	0.185	0.210	0.197	0.217	0.303

[1] 2-digit sector dummies.
Export: dummy=1 if firm exports.
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.
Weighted Tariff: weighted average - across destination - of tariff levels in a given industry i (4 digit sector) at time t, where weights are the share of world exports to that particular destination in that industry and year.
^{a} significant at 1%, ^{b} significant at 5%, ^{c} significant at 10%.
Notes: Cross-sectional Regressions for firms with more than 5 workers, years 1995-2007. The dependent variable is the average lifetime wage of workers within a firm. Different specifications in the columns. Standard errors, clustered at the level of the firm, are reported in parentheses. 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: Tariff Regressions: *Standard Deviation of Worker Type*, more than 5 workers

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Worker Type: Average Lifetime Wage θ^{LW}					
Weighted Tariff*Export	0.007^b	0.007^b	0.007^b	0.007^b	0.006^b	0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
Weighted Tariff	-0.013^a	-0.012^a	-0.012^a	-0.013^a	-0.011^a	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
Export	-0.059^a	-0.069^a	-0.037^b	-0.062^a	-0.073^a	-0.032^b
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.013)
N.Occ.		0.011^a	0.031^a	0.013^a	0.010^a	0.025^a
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
log empl			-0.108^a			-0.022^a
			(0.004)			(0.003)
log dom.share				-0.007^a		0.005^a
				(0.002)		(0.001)
log VA per worker					0.047^a	0.103^a
					(0.006)	(0.004)
white share						0.480^a
						(0.010)
log N. Products						0.014^a
						(0.002)
Avg Lifetime Wage						-0.727^a
						(0.010)
Sector[1]-Year	y	y	y	y	y	y
Obs.	48,280	48,280	48,280	48,280	48,280	48,280
R^2	0.068	0.071	0.094	0.072	0.074	0.550

[1] 2-digit sector dummies.
Export: dummy=1 if firm exports.
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. Lifetime Wage: workers' lifetime wage, averaged by firm.
Weighted Tariff: weighted average - across destination - of tariff levels in a given industry i (4 digit sector) at time t, where weights are the share of world exports to that particular destination in that industry and year.
^{a} significant at 1%, ^{b} significant at 5%, ^{c} significant at 10%.
Notes: Cross-sectional Regressions for firms with more than 5 workers, years 1995-2007. The dependent variable is the dispersion across lifetime wages of workers within a firm. Different specifications in the columns. Standard errors, clustered at the level of the firm, are reported in parentheses. 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 Additional Empirical Results

Table A1: *Summary Statistics*

	Mean	Median	Std Deviation
Avg. Lifetime wage	9.57	9.66	0.61
Avg. Lifetime wage[a]	9.64	9.70	0.43
Std Dev. Lifetime wage	0.62	0.51	0.42
Std Dev. Lifetime wage[a]	0.63	0.53	0.38
Num. Occupation	2.79	2.00	2.04
Domestic Market Share	0.02	0.003	0.06
Employment	137.11	49.00	453.27
Products	14.36	5.00	27.89
Share of Non Production Worker	0.30	0.23	0.33
Value Added per worker	68.55	43.32	180.25

[a] Conditioning on a sample of firms with more than 5 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: Wage Inequality Decomposition

	Conditional Wage Components	
	1995	2007
Between-Firm	41.6%	37.2%
Within-Firm	52.0%	57.7%
Worker Observables	7.6%	4.7%
Cov. observables-firm	-1.3%	0.3%

Note: Wage Variance decomposition from a Mincerian equation that controls for worker observables (in-firm tenure, gender, and occupation dummies) and firm fixed effects.

Table A4: *Rank Correlation Matrix*, Proxies for Firms' Types

	ψ	$Avg\theta_j^{AKM}$	$Avg\theta_j^{LW}$	Dom Share	VA pw	Empl
ψ	1					
$Avg\theta_j^{AKM}$	-0.80	1				
$Avg\theta_j^{LW}$	0.13	0.35	1			
Dom Share	0.01	0.08	0.20	1		
VA per worker	0.001	0.05	0.13	0.64	1	
Empl	-0.01	0.06	0.12	0.78	0.72	1

ψ: Firms' fixed effects, from the AKM decomposition.
$Avg\theta_j^{LW}$: average of the workers' lifetime wages at firm j.
$Avg\theta_j^{AKM}$: Average of workers' fixed effects by firm, from the AKM decomposition, at firm j
VA per worker: Average value added per worker, normalized by 4-digit industries.
Dom Share: Average domestic market share at a 4-digit level.
Empl: Average employment, normalized by 4-digit industries.
Notes: Rank correlation between proxies of firm types. We do not report the p-values but all rank correlations are significantly different from zero.

Table A5: Measuring Sorting Patterns, Manufacturing Sectors

			(4)	(5)	(6)	(7)
			ψ, $Avg\theta_j^{AKM}$		$Avg.$ Share, $Avg\theta_j^{LW}$	
NAF	Industry Label	No Firms	ρ_S [1]	p-val [2]	ρ_S [1]	p-val [2]
10	Food	9	-0.96	0.00	-	-
11	Beverage	8	-1	-	-	-
12	Tobacco prods	-	-	-	-	-
13	Textiles	-	-	-	-	-
14	Clothing	270	-0.84	0.00	0.18	0.00
15	Leather/shoes	-	-	-	-	-
17	Paper	1317	-0.85	0.00	0.14	0.00
18	Printing	1286	-0.86	0.00	0.14	0.00
19	Refining	402	-0.88	0.00	0.42	0.00
20	Chemical	666	-0.86	0.00	0.17	0.00
21	Pharma	780	-0.79	0.00	0.30	0.01
22	Plastics	2070	-0.76	0.00	0.13	0.00
23	Non-metallic prods	59	-0.64	0.00	0.13	0.33
24	Metalworking	1565	-0.72	0.00	0.33	0.00
25	Metal prods	1987	-0.83	0.00	0.25	0.00
26	Info/elec/opt	947	-0.82	0.00	0.27	0.00
27	Elec equip	595	-0.84	0.00	0.14	0.00
28	Machinery	5433	-0.81	0.00	0.21	0.00
29	Automotive	2898	-0.82	0.00	0.28	0.00
30	Other trans equip	126	-0.74	0.00	0.16	0.07
31	Furniture	969	-0.81	0.00	0.25	0.00
32	Other mfg	878	-0.71	0.00	0.13	0.00
33	Repairs	1197	-0.79	0.00	0.23	0.00
	Manufacturing	23388	-0.80	0.00	0.20	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, ($Avg\,\theta^{AKM}$), and the firm fixed effect (ψ) from an AKM decomposition including a quartic polynomial in experience, a dummy for workers residing in Île-de-France, time dummies and all the interactions with the gender dummy.

Columns (6)-(7): Rank correlation and significance level between the average lifetime wage of workers, ($Avg\,\theta^{LW}$), and the firm type, proxied by the average domestic market share in 4-digit sectors $Avg.$ Share.

Table A6: Pooled Cross-sectional Regressions: Standard Deviation of Worker Type (only newly hired workers)

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Worker Type: Average Lifetime Wage θ^{LW}					
Export	-0.025	-0.048^{b}	-0.057^{a}	-0.063^{a}	-0.056^{a}	-0.057^{a}
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.017)
N.Occ.		0.031^{a}	0.024^{a}	0.022^{a}	0.030^{a}	0.0198^{a}
		(0.003)	(0.002)	(0.002)	(0.003)	(0.002)
log empl		-0.028^{a}			-0.031^{a}	-0.023^{a}
		(0.007)			(0.008)	(0.006)
log dom.share			-0.0002		0.002	0.004^{c}
			(0.003)		(0.003)	(0.002)
log VA per worker				0.038^{a}	0.038^{a}	0.048^{a}
				(0.010)	(0.010)	(0.008)
white share						0.332^{a}
						(0.019)
log N. Products						0.018^{a}
						(0.004)
Avg. Lifetime Wage						-0.444^{a}
						(0.011)
Sector-Year	y	y	y	y	y	y
Obs.	14,971	14,971	14,971	14,971	14,971	14,971
R^2	0.154	0.168	0.166	0.168	0.169	0.483

Export: dummy=1 if firm exports.
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. Lifetime Wage: workers' lifetime wage, averaged by firm.
Legend: ^{a} significant at 1%, ^{b} significant at 5%, ^{c} significant at 10%.
Notes: Cross-sectional Regressions for firms with more than 5 workers, years 1995-2007. The dependent variable is the dispersion across lifetime wages of workers within a firm. Different specifications in the columns. Standard errors, clustered at the level of the firm, are reported in parentheses. 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: Pooled Cross-sectional Regressions: *Interquartile Range*, more than 5 workers

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Worker Type: Average Lifetime Wage θ^{LW}					
Export	-0.083^a	-0.010	-0.049^a	-0.073^a	-0.021	-0.024^b
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.012)
N.Occ.		0.019^a	-0.012^a	-0.016^a	0.016^a	0.005^a
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
log empl		-0.178^a			-0.179^a	-0.068^a
		(0.007)			(0.007)	(0.006)
log dom.share			-0.011^a		0.003	0.004^a
			(0.002)		(0.002)	(0.002)
log VA per worker				0.084^a	0.079^a	0.142^a
				(0.010)	(0.010)	(0.007)
white share						0.789^a
						(0.019)
log N. Products						0.019^a
						(0.003)
Avg. Lifetime Wage						-0.930^a
						(0.016)
Sector-Year	y	y	y	y	y	y
Obs.	57,469	57,469	57,469	57,469	57,469	57,469
R^2	0.056	0.094	0.062	0.066	0.099	0.493

Export: dummy=1 if firm exports.
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. Lifetime Wage: workers' lifetime wage, averaged by firm.
^{a} significant at 1%, ^{b} significant at 5%, ^{c} significant at 10%.
Notes: Cross-sectional Regressions for firms with more than 5 workers, years 1995-2007. The dependent variable is the interquartile range across lifetime wages of workers within a firm. Different specifications in the columns. Standard errors, clustered at the level of the firm, are reported in parentheses. 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 A8: Pooled Cross-Section Regressions: *90-10 interdecile range of Worker Type*, more than 5 workers.

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Worker Type: Average Lifetime Wage θ^{LW}					
Export	-0.193^a	-0.025	-0.107^a	-0.170^a	-0.038	-0.045^c
	(0.027)	(0.028)	(0.028)	(0.028)	(0.028)	(0.024)
N.Occ		0.063^a	-0.008^b	-0.020^a	0.061^a	0.043^a
		(0.005)	(0.004)	(0.004)	(0.004)	(0.003)
log empl		-0.434^a			-0.433^a	-0.218^a
		(0.014)			(0.014)	(0.011)
log dom.share			-0.038^a		0.000	0.004
			(0.005)		(0.005)	(0.004)
log VA per worker				0.118^a	0.111^a	0.258^a
				(0.018)	(0.017)	(0.014)
white share						1.339^a
						(0.034)
log N. Products						0.038^a
						(0.006)
Avg Lifetime Wage						-1.831^a
						(0.025)
Sector-Year	y	y	y	y	y	y
Obs.	57,469	57,469	57,469	57,469	57,469	57,469
R^2	0.059	0.115	0.067	0.067	0.117	0.495

Export: dummy=1 if firm exports.
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. Lifetime Wage: workers' lifetime wage, averaged by firm.
^{a} significant at 1%, ^{b} significant at 5%, ^{c} significant at 10%.
Notes: Cross-Sectional Regressions for firms with more than 5 workers, years 1995-2007. The dependent variable is the 90-10 interdecile range across lifetime wages of workers within a firm. Different specifications in the columns. Standard errors, clustered at the level of the firm, are reported in parentheses. 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 A9: IV Regressions: *Average and Standard Deviation of Worker Type*, more than 5 workers. The instrument is based on export shares in 1995.

	Worker Type: Avg Lifetime Wage					
	IV based on Exp Share in 1995					
	Avg Workers Type			*Std Dev Workers Type*		
	(1)	(2)	(3)	(4)	(5)	(6)
Export	0.244^a	0.062^c	0.242^b	-0.074^a	-0.093^a	-0.233^a
	(0.028)	(0.034)	(0.097)	(0.026)	(0.033)	(0.074)
N. Occ		0.006	-0.002		0.031^a	0.023^a
		(0.004)	(0.004)		(0.003)	(0.003)
log empl		0.137^a	0.144^a		-0.099^a	-0.016^c
		(0.013)	(0.012)		(0.012)	(0.008)
log dom share		0.003	0.002		0.011^a	0.010^a
		(0.004)	(0.004)		(0.003)	(0.002)
log VA per worker		0.196^a	0.136^a		0.028^b	0.110^a
		(0.014)	(0.014)		(0.011)	(0.009)
white share			0.558^a			0.436^a
			(0.033)			(0.023)
log N. Products			-0.058^b			0.068^a
			(0.024)			(0.018)
Avg Lifetime Wage						-0.736^a
						(0.017)
Sector-Year	y	y	y	y	y	y
Obs	12,844	12,844	12,844	12,844	12,844	12,844
R^2	0.214	0.308	0.368	0.052	0.076	0.536

Export: dummy=1 if firm exports.
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. Lifetime Wage: workers' lifetime wage, averaged by firm.
^{a} significant at 1%, ^{b} significant at 5%, ^{c} significant at 10%.
Notes: IV Regressions for firms with more than 5 workers, years 1995-2007. The dependent variable is the dispersion across lifetime wages of workers within a firm. Export status is instrumented using tariffs and the export share in the initial year. Standard errors, clustered at the level of the firm, are reported in parentheses. 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 A10: IV Regressions: *Standard Deviation of Worker Type*, adjusted by occupation composition, more than 5 workers

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Worker Type: Average Lifetime Wage θ^{LW}					
	Exp Share$_{t-1}$			Exp Share$_{t-3}$		
Export	-0.025^{c}	-0.052^{a}	-0.149^{a}	0.014	-0.045^{a}	-0.159^{a}
	(0.013)	(0.015)	(0.035)	(0.012)	(0.015)	(0.040)
N.Occ.		0.019^{a}	0.016^{a}		0.019^{a}	0.017^{a}
		(0.001)	(0.002)		(0.002)	(0.002)
log empl		-0.021^{a}	-0.026^{a}		-0.022^{a}	-0.026^{a}
		(0.005)	(0.005)		(0.005)	(0.005)
log dom.share		0.003^{b}	0.002^{c}		0.002	0.002
		(0.001)	(0.001)		(0.001)	(0.001)
log VA per worker		-0.006	0.015^{a}		-0.012^{b}	0.009^{b}
		(0.005)	(0.004)		(0.005)	(0.005)
white share			-0.163^{a}			-0.178^{a}
			(0.014)			(0.015)
log N. Products			0.033^{a}			0.035^{a}
			(0.008)			(0.010)
Avg. Lifetime Wage			0.014^{a}			0.012^{a}
			(0.002)			(0.002)
Sector-Year	y	y	y	y	y	y
Obs.	15,180	15,180	15,180	12,482	12,482	12,482
R^2	0.068	0.095	0.137	0.053	0.098	0.142

Export: dummy=1 if firm exports.
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. Lifetime Wage: workers' lifetime wage, averaged by firm.
^{a} significant at 1%, ^{b} significant at 5%, ^{c} significant at 10%.
Notes: IV Regressions for firms with more than 5 workers, years 1995-2007. The dependent variable is constructed as a weighted average of the standard deviation of ability among different groups of workers (executives, managers, and blue collars); the weights are the average employment in a specific occupation category. Export status is instrumented using tariffs and the previous year export share in columns (1)-(3); columns (4)-(6) use the $t-3$ export share. Standard errors, clustered at the level of the firm, are reported in parentheses. 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 A11: Pooled Cross-Section Regressions: *Average Worker Type*, more than 5 workers, controlling for the share of imported inputs.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Worker Type: Average Lifetime Wage θ^{LW}					
Export	0.145^a	0.061^a	0.063^a	0.078^a	0.039^a	0.026^b
	(0.012)	(0.012)	(0.012)	(0.011)	(0.011)	(0.013)
Sh Imported Input	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N.Occ		0.018^a	0.033^a	0.035^a	0.013^a	-0.002
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
log empl		0.112^a			0.109^a	0.115^a
		(0.006)			(0.006)	(0.006)
log dom.share			0.026^a		0.005^b	0.004^c
			(0.002)		(0.002)	(0.002)
log VA per worker				0.165^a	0.163^a	0.104^a
				(0.008)	(0.008)	(0.008)
white share						0.524^a
						(0.019)
log N. Products						0.007^b
						(0.003)
Sector-Year	y	y	y	y	y	y
Obs.	55,584	55,584	55,584	55,584	55,584	55,584
R^2	0.136	0.201	0.190	0.214	0.236	0.301

Export: dummy=1 if firm exports.
Sh Imported Inputs: share of imported inputs out of total material purchases.
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.
^{a} significant at 1%, ^{b} significant at 5%, ^{c} significant at 10%.
Notes: Cross-Sectional Regressions for firms with more than 5 workers, years 1995-2007. The dependent variable is the average lifetime wage of workers within a firm. Different specifications in the columns. Standard errors, clustered at the level of the firm, are reported in parentheses. 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 A12: Pooled Cross-Section Regressions: *Standard Deviation of Worker Type*, more than 5 workers, controlling for the share of imported inputs.

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Worker Type: Average Lifetime Wage θ^{LW}					
Export	-0.041^a	-0.020^c	-0.041^a	-0.057^a	-0.024^b	-0.022^b
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)
Sh Imported Inputs	0.000	0.000	0.000	0.000	0.000	0.000^b
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N.Occ		0.031^a	0.013^a	0.010^a	0.030^a	0.024^a
		(0.002)	(0.001)	(0.001)	(0.002)	(0.001)
log empl		-0.106^a			-0.106^a	-0.022^a
		(0.005)			(0.005)	(0.004)
log dom.share			-0.009^a		0.000	0.002
			(0.002)		(0.002)	(0.001)
log VA per worker				0.045^a	0.043^a	0.108^a
				(0.006)	(0.006)	(0.005)
white share						0.487^a
						(0.012)
log N. Products						0.013^a
						(0.00238)
Avg Lifetime Wage						-0.736^a
						(0.009)
Sector-Year	y	y	y	y	y	y
Obs.	55,584	55,584	55,584	55,584	55,584	55,584
R^2	0.064	0.090	0.068	0.070	0.093	0.545

Export: dummy=1 if firm exports.
Sh Imported Inputs: share of imported inputs out of total material purchases.
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. Lifetime Wage: workers' lifetime wage, averaged by firm.
^{a} significant at 1%, ^{b} significant at 5%, ^{c} significant at 10%.
Notes: Cross-Sectional Regressions for firms with more than 5 workers, years 1995-2007. The dependent variable is the dispersion across lifetime wages of workers within a firm. Different specifications in the columns. Standard errors, clustered at the level of the firm, are reported in parentheses. 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 A13: Pooled GLS Regressions: Average Worker Type

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Worker Type: Average Lifetime Wage θ^{LW}					
Export	0.174^a	0.047^a	0.050^a	0.072^a	0.021^b	-0.009
	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)	(0.012)
N.Occ.		-0.004	0.013^a	0.019^a	-0.006^b	-0.009^a
		(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
log empl		0.097^a			0.085^a	0.075^a
		(0.007)			(0.006)	(0.006)
log dom.share			0.032^a		0.006^a	0.004^b
			(0.003)		(0.002)	(0.002)
log VA per worker				0.177^a	0.167^a	0.103^a
				(0.010)	(0.009)	(0.009)
white share						0.559^a
						(0.022)
log N. Products						0.014^a
						(0.004)
Sector-Year	y	y	y	y	y	y
Obs.	148,784	148,784	148,784	148,784	148,784	148,784
R^2	0.181	0.253	0.244	0.268	0.289	0.360

Export: dummy=1 if firm exports.
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.
^{a} significant at 1%, ^{b} significant at 5%, ^{c} significant at 10%.
Notes: Cross-sectional GLS Regressions for firms with more than 5 workers, years 1995-2007. The dependent variable is the average lifetime wage of workers within a firm. Different specifications in the columns. Standard errors, clustered at the level of the firm, are reported in parentheses. 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 A14: Pooled GLS Regressions: Standard Deviation of Worker Type

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Worker Type: Average Lifetime Wage θ^{LW}					
Export	-0.017	-0.017	-0.038^{a}	-0.050^{a}	-0.025^{b}	-0.035^{a}
	(0.011)	(0.012)	(0.012)	(0.012)	(0.012)	(0.010)
N.Occ.		0.024^{a}	0.012^{a}	0.010^{a}	0.024^{a}	0.017^{a}
		(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
log empl		-0.055^{a}			-0.060^{a}	-0.004
		(0.009)			(0.008)	(0.006)
log dom.share			-0.004		0.004^{c}	0.006^{a}
			(0.003)		(0.002)	(0.002)
log VA per worker				0.037^{a}	0.040^{a}	0.095^{a}
				(0.008)	(0.009)	(0.007)
white share						0.508^{a}
						(0.016)
log N. Products						0.014^{a}
						(0.003)
Avg. Lifetime Wage						-0.713^{a}
						(0.012)
Sector-Year	y	y	y	y	y	y
Obs.	88,790	88,790	88,790	88,790	88,790	88,790
R^2	0.099	0.119	0.108	0.111	0.123	0.553

Export: dummy=1 if firm exports.
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. Lifetime Wage: workers' lifetime wage, averaged by firm.6 codes). This variable is zero for non-exporters.
Avg. Lifetime Wage: workers' lifetime wage, averaged by firm.
^{a} significant at 1%, ^{b} significant at 5%, ^{c} significant at 10%.
Notes: Cross-sectional GLS Regressions for firms with more than 5 workers, years 1995-2007. The dependent variable is the dispersion across lifetime wages of workers within a firm. Different specifications in the columns. Standard errors, clustered at the level of the firm, are reported in parentheses. 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 A15: Pooled Cross-Section Regressions: *Average Worker Type*, more than 5 workers. Weighted regression by average experience in the firm.

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Worker Type: Average Lifetime Wage θ^{LW}					
Export	0.090^a	0.033^a	0.026^b	0.035^a	0.010	0.008
	(0.011)	(0.011)	(0.011)	(0.010)	(0.010)	(0.012)
N.Occ		0.014^a	0.023^a	0.023^a	0.009^a	-0.007^a
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
log empl		0.072^a			0.070^a	0.080^a
		(0.006)			(0.006)	(0.005)
log dom.share			0.021^a		0.003	0.0030
			(0.002)		(0.002)	(0.002)
log VA per worker				0.184^a	0.182^a	0.122^a
				(0.008)	(0.008)	(0.008)
white share						0.538^a
						(0.016)
log N. Products						0.002
						(0.003)
Sector-Year y	y	y	y	y	y	y
Obs.	57,206	57,206	57,206	57,206	57,206	57,206
R^2	0.163	0.208	0.205	0.247	0.260	0.342

Export: dummy=1 if firm exports.
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.
^{a} significant at 1%, ^{b} significant at 5%, ^{c} significant at 10%.
Notes: Cross-Sectional Regressions for firms with more than 5 workers, years 1995-2007; the observations are weighted by the average experience of workers within the firm. The dependent variable is the average lifetime wage of workers within a firm. Different specifications in the columns. Standard errors, clustered at the level of the firm, are reported in parentheses. 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 A16: Pooled Cross-Section Regressions: *Standard Deviation of Worker Type*, more than 5 workers. Weighted regression by average experience in the firm.

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Worker Type: Average Lifetime Wage θ^{LW}					
Export	-0.011	-0.009	-0.024[b]	-0.037[a]	-0.014	-0.028[a]
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.010)
N.Occ		0.035[a]	0.021[a]	0.019[a]	0.034[a]	0.025[a]
		(0.002)	(0.002)	(0.001)	(0.002)	(0.001)
log empl		-0.082[a]			-0.082[a]	-0.020[a]
		(0.006)			(0.006)	(0.005)
log dom.share			-0.006[a]		0.000	0.001
			(0.002)		(0.002)	(0.002)
log VA per worker				0.046[a]	0.045[a]	0.128[a]
				(0.006)	(0.007)	(0.006)
white share						0.527[a]
						(0.014)
log N. Products						0.012[a]
						(0.003)
Avg Lifetime Wage						-0.779[a]
						(0.009)
Sector-Year	y	y	y	y	y	y
Obs.	57,206	57,206	57,206	57,206	57,206	57,206
R^2	0.048	0.077	0.062	0.065	0.080	0.503

Export: dummy=1 if firm exports.
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. Lifetime Wage: workers' lifetime wage, averaged by firm.
[a] significant at 1%, [b] significant at 5%, [c] significant at 10%.
Notes: Cross-Sectional Regressions for firms with more than 5 workers, years 1995-2007; the observations are weighted by the average experience of workers within the firm. The dependent variable is the dispersion across lifetime wages of workers within a firm. Different specifications in the columns. Standard errors, clustered at the level of the firm, are reported in parentheses. 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.

B Online Appendix

B.1 Theoretical Framework

The setting is borrowed from Eeckhout and Kircher (2011), a dynamic model in which 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 θ is distributed according to a smooth density $g(\theta)$ on the interval $[0,1]$, while a firm's type ψ 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 $\sigma > 0$. Although standard in this literature (see for example one of most recent advances by Hagedorn et al., 2017), the restriction of one worker per firm deserves some justification. Of course this choice is done for tractability in order to isolate the hiring decision of each individual worker. It is obvious, though, that hiring decisions of different workers interact for several reasons. First, when a firm is facing a downward-sloping demand, resulting in revenues being concave in output, the marginal revenue of each match depends on other hires. Second, there may be complementarities among workers in the production function. The problem of choosing quantity and quality of workers in a multi-worker firm has been tackled by Eeckhout and Kircher (2016) and Grossman et al. (2017). Importantly their setup is one *without frictions* and in equilibrium each firm (manager) matches with only one type of worker, thus eliminating the possibility of any intra-firm type dispersion, which is the focus of our empirical analysis. As far as we know, there exists no model that explores the optimal matching of firms/managers with multiple workers in the presence of frictions, which we deem necessary to generate within-firm worker type dispersion in equilibrium. We suspect such a model would be very difficult to solve and an important contribution per se, well beyond the scope of this paper.

We embed the matching problem in a monopolistic competition model à la Krugman (1979).

Each firm produces a differentiated variety of a product. Demand for an individual variety is isoelastic with elasticity $\eta > 1$. Therefore, firms selling their output in the domestic market obtain total revenues

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

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

In the absence of frictions, we would observe perfect positive assortative matching and every type of firm 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 ψ, as in Sampson (2014).

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 proposed by Eeckhout and Kircher (2011).[34] There are two periods. In the first period, workers and firms meet at random, perfectly observe one another's type and decide whether to produce. If the agents agree to match, they leave the market and split the revenues according to Nash Bargaining, with a fraction γ accruing to the worker and a complementary fraction $(1-\gamma)$ captured by the firm; in what follows, we abstract from differences in bargaining power and set $\gamma = 1/2$. If the agents do not produce, they pay a cost c to search again in the second period. In the second period,[35] 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

[34] Extending the model to an infinite horizon framework does not alter the qualitative predictions of the equilibrium. The analytical characterization, however, requires that workers and firms have the same distribution.

[35] We interpret the second period as the *future* in an infinite horizon framework. In fact, the frictionless payoffs share qualitative properties with the continuation values derived in an infinite horizon model.

simple setup.

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. (2017). In both U.S. 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.[36]

Similarly to Helpman et al. (2017), in our exercise we focus on the effect of exporting separately from that of firm productivity; therefore, we allow 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.[37]

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

[36] See figure B5.

[37] Perhaps more importantly, we do not want to introduce further complication when the data points against it. In our data set, the entry and exit margin in the export market seems to be quite inactive. When firms are present in the sample, they either export or they do not.

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 ψ that exports can be written as follows:

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

where E_x is foreign real expenditure.

It is straightforward to verify that, for given θ and ψ, 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 given productivity ψ as follows:

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

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

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

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

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 the *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, $\varphi = A_i\psi$, and assume that such distribution $h(\varphi)$ is uniform. We assume that the distribution of worker types $g(\theta)$ is also uniform, as in Eeckhout and Kircher (2011).

B.2 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; then, we analyze first period firms' and workers' decisions. Once again, the problem is analyzed in terms of the *adjusted* firm type φ and of the worker type θ. We rewrite the revenue function as $R(\theta, \varphi) = (\theta\varphi)^{\alpha}$ where $\alpha = \frac{\sigma(\eta-1)}{\eta}$.

B.2.1 Second Period: Frictionless Market

In the second period, assignment is positive assortative. The matching function, $\mu(\theta) = \varphi$, which assigns firm φ to worker θ, 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

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

By symmetry, equilibrium profits in the second period take the same form:

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

B.2.2 Acceptance Sets

We now determine the matching behavior of firms and workers in the first period. When a worker θ and a firm φ 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:

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

The surplus condition (B.5) defines the acceptance set, i.e. the set of pairs (θ, φ) sharing a mutually acceptable match. The set of workers that match with firm φ are denoted by $A(\varphi)$. The boundaries of the set $A(\varphi)$ are shown by Eeckhout and Kircher (2011) to be monotonically increasing in φ, which proves that positive assortative matching holds in the presence of constant search costs.[38] Let us define $u(\varphi)$ and $l(\varphi)$, respectively, the highest and the lowest worker types that match with firm type φ. Figure B1 illustrates the acceptance set for $\alpha = 1$ and $c = 0.01$, but in general $u(\varphi)$ and $l(\varphi)$ are not parallel.

B.2.3 Exporting and the Width of the Acceptance Set

We now investigate whether exporting (or more productive) firms tolerate higher or lower variation in the set of workers with which they match. We adopt the *matching range* of firm type φ, $d(\varphi)$, as a measure of the dispersion of worker types tolerated by the firm. The matching range $d(\varphi)$ is defined as the difference between $u(\varphi)$ and $l(\varphi)$ and may be an increasing or decreasing function of φ. At this point it is important to discuss whether the absolute measure $d(\varphi)$ is appropriate for the sake of comparing to comparing the dispersion of worker types within firms that exhibit

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

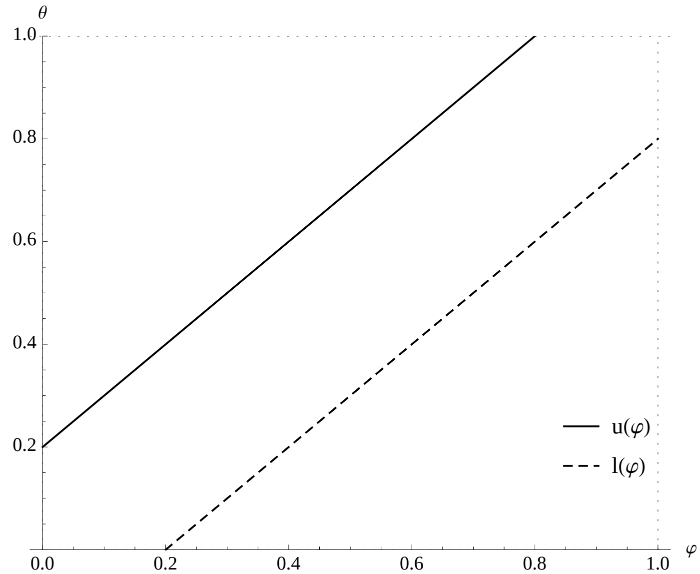

Figure B1: Acceptance Set with $\alpha = 1$, $c = 0.01$

differences also in the average type of worker hired. Let us take, for example, the parametrization in figure B1 and consider two firms. Firm φ_H hires, on average, very high worker types and firm φ_L hires, on average, very low worker types. Figure B1 implies that we should observe the same $d(\varphi)$ for both firms, but we would probably not conclude that the two firms tolerate the same degree of worker variation. This is because, in relative terms, firm φ_H tolerates less variation relative to the average worker hired than firm φ_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 φ, $a(\varphi)$. 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* $d_2(\varphi)$, a measure defined on a logarithmic scale so that dispersion is defined in relative revenue deviations. Define $d_2(\varphi) = u_2(\varphi) - l_2(\varphi)$ 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 B.1 *Dispersion of worker types working at firm φ, as measured by*

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

(ii) the logarithmic matching range $d_2(\varphi)$

is decreasing in firm type (and is therefore lower for exporting firms relative to non-exporting firms of identical initial 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 φ. Similarly, one can show that $l_1(\varphi)$ is an increasing function of φ. Therefore, the difference between $u_1(\varphi)$ and $l_1(\varphi)$ is decreasing.

(ii) In order to prove that $d_2(\varphi)$ is decreasing, we are going to show that $\frac{d\,u_2(\varphi)}{d\ln\varphi} < 1$ and that $\frac{d\,l_2(\varphi)}{d\ln\varphi} > 1$. 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 $\frac{dl_2(\varphi)}{d\ln\varphi} > 1$. ■

It is easy to show that this proposition holds more in general as long as the production function is increasing, symmetric, homogeneous, and supermodular. Figure B2 presents the two normalized measures with the same parametrization as in figure B1.

The result in proposition 1 is easy to explain once we express the surplus condition (B.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 φ. Condition (B.5) can be rewritten as a function of $\widehat{\theta}$ as follows:

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

We analyze the behavior of the function $S\left(\widehat{\theta},\varphi\right)$ and the search costs in figure B3. The function

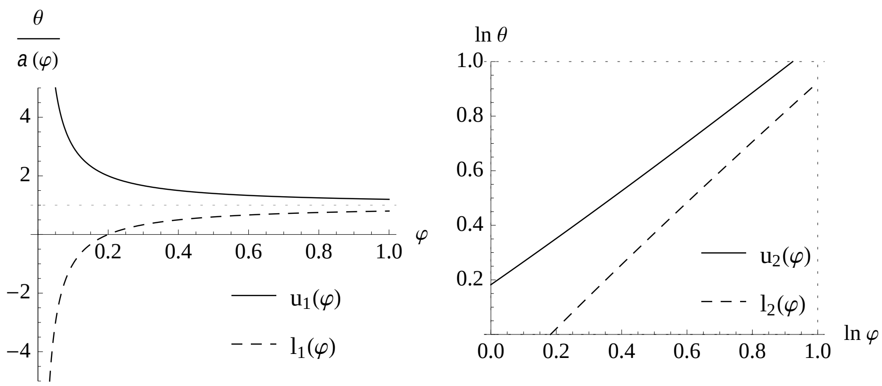

Figure B2: Normalized Matching Range with $\alpha = 1$, $c = 0.01$

$S\left(\widehat{\theta}, \varphi\right)$ 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 φ 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 B3 clearly shows.

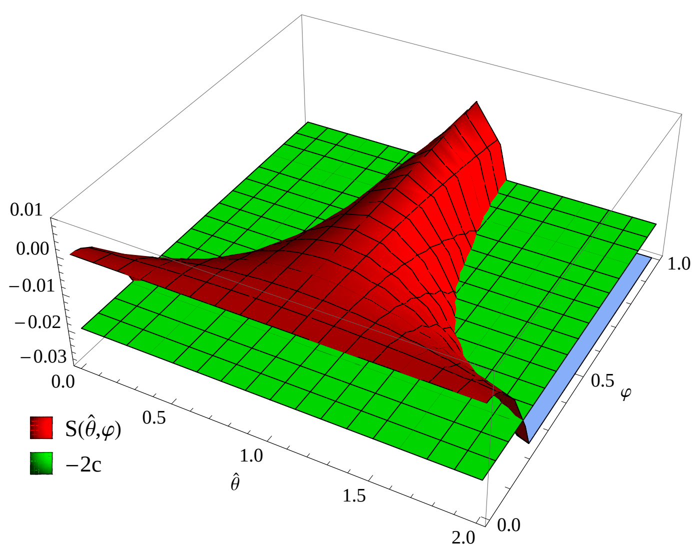

Figure B3: Surplus Condition as a Function of Normalized Worker Types for $\alpha = 1$, $c = 0.01$

B.3 Identification of Worker Type: Average Lifetime Wage

Agents' types are positively correlated with the average realization of their payoffs over their job spells. In particular, a more productive worker makes a larger contribution to revenues and tends to match with a better firm in the frictionless equilibrium, obtaining, on average, a higher payoffs. Following the model, we propose to identify the agents' type using the average wage. In fact, there exists a well-defined relation. In fact, the average wage of a worker of type θ,

$$\begin{aligned}
\bar{w}\left(\theta\right) &= \frac{1}{\left(\theta^{\alpha}+2\sqrt{c}\right)^{1/\alpha}-\left(\theta^{\alpha}-2\sqrt{c}\right)^{1/\alpha}}\int_{\left(\theta^{\alpha}-2\sqrt{c}\right)^{1/\alpha}}^{\left(\theta^{\alpha}+2\sqrt{c}\right)^{1/\alpha}}\left[\frac{\theta^{2\alpha}}{4}+\frac{\theta^{\alpha}y^{\alpha}}{2}-\frac{y^{2\alpha}}{4}\right]\mathrm{d}y \\
&= \frac{\theta^{2\alpha}}{4}+\frac{\theta^{\alpha}\left[\left(\theta^{\alpha}+2\sqrt{c}\right)^{\frac{\alpha+1}{\alpha}}-\left(\theta^{\alpha}-2\sqrt{c}\right)^{\frac{\alpha+1}{\alpha}}\right]}{2\left(\alpha+1\right)\left[\left(\theta^{\alpha}+2\sqrt{c}\right)^{\frac{1}{\alpha}}-\left(\theta^{\alpha}-2\sqrt{c}\right)^{\frac{1}{\alpha}}\right]}-\frac{\left(\theta^{\alpha}+2\sqrt{c}\right)^{\frac{2\alpha+1}{\alpha}}-\left(\theta^{\alpha}-2\sqrt{c}\right)^{\frac{2\alpha+1}{\alpha}}}{4\left(2\alpha+1\right)\left[\left(\theta^{\alpha}+2\sqrt{c}\right)^{\frac{1}{\alpha}}-\left(\theta^{\alpha}-2\sqrt{c}\right)^{\frac{1}{\alpha}}\right]}
\end{aligned}$$

In particular, if $\alpha=1$,

$$\bar{w}\left(\theta\right)=\frac{\theta^{2}}{4}-\frac{c}{3}$$

If the demand elasticity α and the search cost c were known, we could back up exactly the worker types. In order to prove that the average wage is increasing in θ, we'll break the proof into two parts. First, it is trivial to prove that the outside option is increasing in the worker type. The second part of the proof will show that a worker of higher ability generates a larger surplus and obtains a larger share of it. In the two-period model, under the assumption of a uniform distribution,

$$
\begin{aligned}
\frac{\int_{l(\theta)}^{u(\theta)} s(\theta, y)\,\mathrm{d}y}{\int_{l(\theta)}^{u(\theta)} \mathrm{d}y} &= \frac{\int_{(\theta^\alpha - 2\sqrt{c})^{1/\alpha}}^{(\theta^\alpha + 2\sqrt{c})^{1/\alpha}} \left[\theta^\alpha \cdot y^\alpha - \frac{\theta^{2\alpha}}{2} - \frac{y^{2\alpha}}{2}\right] \mathrm{d}y}{(\theta^\alpha + 2\sqrt{c})^{1/\alpha} - (\theta^\alpha - 2\sqrt{c})^{1/\alpha}} \\
&= \frac{y\left[\frac{\theta^\alpha \cdot y^\alpha}{\alpha+1} - \frac{\theta^{2\alpha}}{2} - \frac{y^{2\alpha}}{2(2\alpha+1)}\right]\Big|_{(\theta^\alpha - 2\sqrt{c})^{1/\alpha}}^{(\theta^\alpha + 2\sqrt{c})^{1/\alpha}}}{(\theta^\alpha + 2\sqrt{c})^{1/\alpha} - (\theta^\alpha - 2\sqrt{c})^{1/\alpha}} \\
&= \frac{y\left[\theta^\alpha \cdot y^\alpha - \frac{\theta^{2\alpha}}{2} - \frac{y^{2\alpha}}{2} + \alpha\frac{\theta^\alpha \cdot y^\alpha}{\alpha+1} + \frac{2\alpha y^{2\alpha}}{2(2\alpha+1)}\right]\Big|_{(\theta^\alpha - 2\sqrt{c})^{1/\alpha}}^{(\theta^\alpha + 2\sqrt{c})^{1/\alpha}}}{(\theta^\alpha + 2\sqrt{c})^{1/\alpha} - (\theta^\alpha - 2\sqrt{c})^{1/\alpha}} \\
&= -2c + \alpha\frac{\left[(\theta^\alpha + 2\sqrt{c})^{\frac{1+\alpha}{\alpha}} - (\theta^\alpha - 2\sqrt{c})^{\frac{1+\alpha}{\alpha}}\right]}{(\theta^\alpha + 2\sqrt{c})^{\frac{1}{\alpha}} - (\theta^\alpha - 2\sqrt{c})^{\frac{1}{\alpha}}} \frac{(3\alpha+2)\,\theta^\alpha}{(\alpha+1)(2\alpha+1)} + \\
&+ \alpha\frac{2\sqrt{c}}{(2\alpha+1)} \frac{\left[(\theta^\alpha + 2\sqrt{c})^{\frac{1+\alpha}{\alpha}} + (\theta^\alpha - 2\sqrt{c})^{\frac{1+\alpha}{\alpha}}\right]}{(\theta^\alpha + 2\sqrt{c})^{\frac{1}{\alpha}} - (\theta^\alpha - 2\sqrt{c})^{\frac{1}{\alpha}}}
\end{aligned}
$$

The surplus is increasing for all $\alpha > 0$. In fact,

$$
\begin{aligned}
\frac{\partial}{\partial\theta}\left[\frac{\left[(\theta^\alpha + 2\sqrt{c})^{\frac{1+\alpha}{\alpha}} - (\theta^\alpha - 2\sqrt{c})^{\frac{1+\alpha}{\alpha}}\right]}{(\theta^\alpha + 2\sqrt{c})^{\frac{1}{\alpha}} - (\theta^\alpha - 2\sqrt{c})^{\frac{1}{\alpha}}}\right] &= \alpha\theta^{\alpha-1}\left[\frac{1+\alpha}{\alpha} - \frac{1}{\alpha}\frac{(\theta^\alpha + 2\sqrt{c})^{\frac{2}{\alpha}} + (\theta^\alpha - 2\sqrt{c})^{\frac{2}{\alpha}}}{\left((\theta^\alpha + 2\sqrt{c})^{\frac{1}{\alpha}} - (\theta^\alpha - 2\sqrt{c})^{\frac{1}{\alpha}}\right)^2}\right] + \\
&+ \alpha\theta^{\alpha-1}\left[\frac{1}{\alpha}\frac{(\theta^\alpha + 2\sqrt{c})^{\frac{1}{\alpha}}(\theta^\alpha - 2\sqrt{c})^{\frac{1}{\alpha}}\left[\frac{\theta^\alpha+2\sqrt{c}}{\theta^\alpha-2\sqrt{c}} + \frac{\theta^\alpha-2\sqrt{c}}{\theta^\alpha+2\sqrt{c}}\right]}{\left((\theta^\alpha + 2\sqrt{c})^{\frac{1}{\alpha}} - (\theta^\alpha - 2\sqrt{c})^{\frac{1}{\alpha}}\right)^2}\right] \\
&= \alpha\theta^{\alpha-1} + \theta^{\alpha-1}\frac{(\theta^\alpha + 2\sqrt{c})^{\frac{1}{\alpha}}(\theta^\alpha - 2\sqrt{c})^{\frac{1}{\alpha}}\left[\frac{\theta^\alpha+2\sqrt{c}}{\theta^\alpha-2\sqrt{c}} + \frac{\theta^\alpha-2\sqrt{c}}{\theta^\alpha+2\sqrt{c}} - 2\right]}{\left((\theta^\alpha + 2\sqrt{c})^{\frac{1}{\alpha}} - (\theta^\alpha - 2\sqrt{c})^{\frac{1}{\alpha}}\right)^2}
\end{aligned}
$$

and

$$
\begin{aligned}
\frac{\partial}{\partial\theta}\left[\frac{\left[(\theta^\alpha + 2\sqrt{c})^{\frac{1+\alpha}{\alpha}} + (\theta^\alpha - 2\sqrt{c})^{\frac{1+\alpha}{\alpha}}\right]}{(\theta^\alpha + 2\sqrt{c})^{\frac{1}{\alpha}} - (\theta^\alpha - 2\sqrt{c})^{\frac{1}{\alpha}}}\right] &= \alpha\theta^{\alpha-1}\left[\frac{(\theta^\alpha + 2\sqrt{c})^{\frac{1}{\alpha}} + (\theta^\alpha - 2\sqrt{c})^{\frac{1}{\alpha}}}{(\theta^\alpha + 2\sqrt{c})^{\frac{1}{\alpha}} - (\theta^\alpha - 2\sqrt{c})^{\frac{1}{\alpha}}}\right] + \\
&+ \alpha\theta^{\alpha-1}\left[\frac{1}{\alpha}\frac{(\theta^\alpha + 2\sqrt{c})^{\frac{1}{\alpha}}(\theta^\alpha - 2\sqrt{c})^{\frac{1}{\alpha}}\left[\frac{\theta^\alpha+2\sqrt{c}}{\theta^\alpha-2\sqrt{c}} - \frac{\theta^\alpha-2\sqrt{c}}{\theta^\alpha+2\sqrt{c}}\right]}{\left((\theta^\alpha + 2\sqrt{c})^{\frac{1}{\alpha}} - (\theta^\alpha - 2\sqrt{c})^{\frac{1}{\alpha}}\right)^2}\right]
\end{aligned}
$$

are both positive.

B.4 Identification of Worker Type: AKM Worker Fixed Effect

Following the analysis and adopting the same notation on pages 885-886 of EK, the worker fixed effect $\delta(x)$ and the firm fixed effect $\psi(y)$ can be written as:

$$\delta(x) = \int_{B(x)} [w(x,y) - \psi(y)]\, d\Upsilon(y|x) \tag{B.7}$$

$$\psi(y) = \int_{A(y)} [w(x,y) - \delta(x)]\, d\Gamma(x|y) \tag{B.8}$$

Substituting equation (B.8) into equation (B.7), the worker fixed effect $\delta(x)$ is determined by the following integral equation:

$$\delta(x) = \int_{B(x)} [w(x,y) - w_{AV}(y)]\, d\Upsilon(y|x) + \int_{B(x)} \int_{A(y)} \delta(t)\, d\Gamma(t|y) d\Upsilon(y|x) \tag{B.9}$$

where $w_{AV}(y) = \int_{A(y)} w(t,y)\, d\Gamma(t|y)$.

Let us look at the specific example of uniformly distributed firms and worker types on the interval $[0,1]$ with a simplified production function $f(x,y) = xy$ where the wage is $w(x,y) = \frac{xy}{2} + \frac{x^2}{4} - \frac{y^2}{4}$ and the acceptance range for a worker x is $y \in [x-k, x+k]$. For simplicity, we focus on the case where $x \in [2k, 1-2k]$ as EK do to avoid boundary cases. Thus, we can write equation

(B.9) as:

$$
\begin{aligned}
\delta(x) &= \int_{x-k}^{x+k} \left(\frac{xy}{2} + \frac{x^2}{4} - \frac{y^2}{4} \right) \frac{1}{2k} dy \\
&- \int_{x-k}^{x+k} \int_{y-k}^{y+k} \left(\frac{ty}{2} + \frac{t^2}{4} - \frac{y^2}{4} \right) \frac{1}{4k^2} dt dy \\
&+ \int_{x-k}^{x+k} \int_{y-k}^{y+k} \delta(t) \frac{1}{4k^2} dt dy \\
&= -\frac{k^2}{3} + \frac{1}{4k^2} \int_{x-k}^{x+k} \int_{y-k}^{y+k} \delta(t)\, dt dy
\end{aligned} \tag{B.10}
$$

with the associated first derivative,

$$
\frac{d\delta(x)}{dx} = \frac{1}{4k^2} \left(\int_{x}^{x+2k} \delta(t)\, dt - \int_{x-2k}^{x} \delta(t)\, dt \right) \tag{B.11}
$$

Equation (B.10) is a Fredhold integral equation of the second kind, for which we could not find an analytical solution, as expected. Notice that solving (B.11) would yield solutions $\delta(x)$ that do not satisfy (B.10). We proceeded by solving (B.10) via the Adomian decomposition, a common numerical approximation method for integral equations.[39] The analysis in the interval $x < 2k$ (which is ignored in EK) is fundamental to obtain a well-behaved solution to the integral equation. Figure B4 shows the solution of $\delta(x)$ for $k = 0.05$.

Alternatively, one can easily verify in a fictional database that while the fixed effect of the firm may go up or down with the type of the firm, the worker fixed effect is monotonically increasing in x, the worker type.

[39] We are happy to share the code upon request.

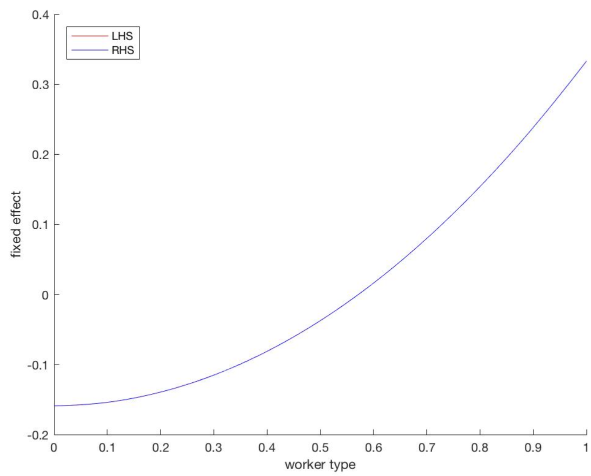

Figure B4: Solution to The Worker Type Differential Equation

B.5 Additional Figures

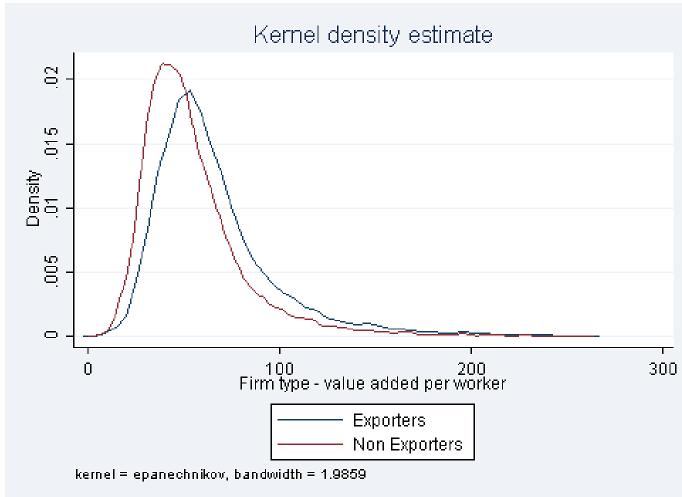

Figure B5: Distribution of Value Added per Worker in Exporting and Non-Exporting Firms

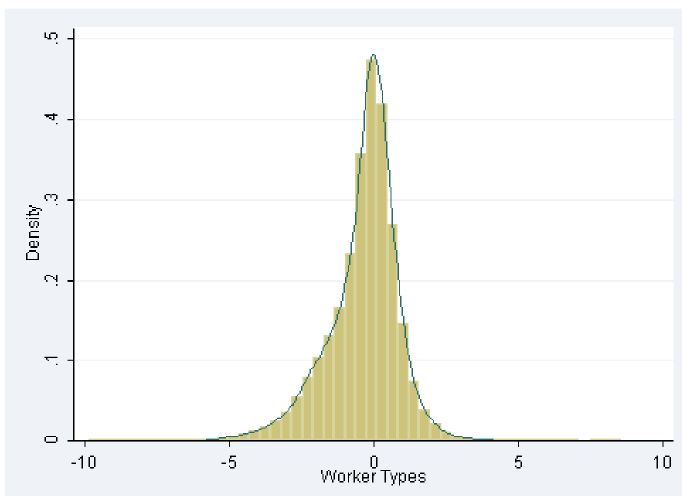

Figure B6: Distribution of Individual Effects, Largest Connected Group

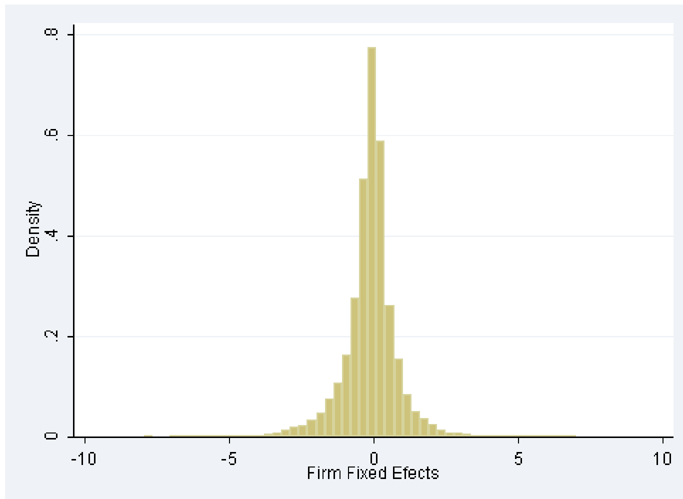

Figure B7: Distribution of Firm Effects, Largest Connected Group

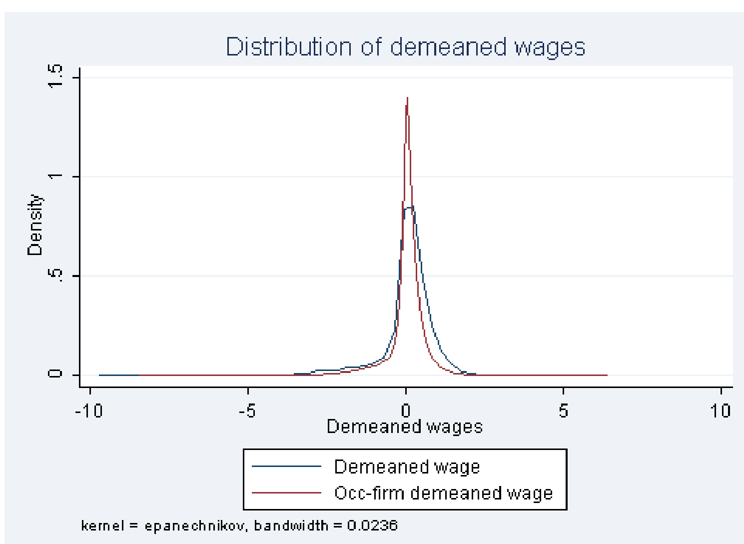

Figure B8: Variability in Wages: Comparison

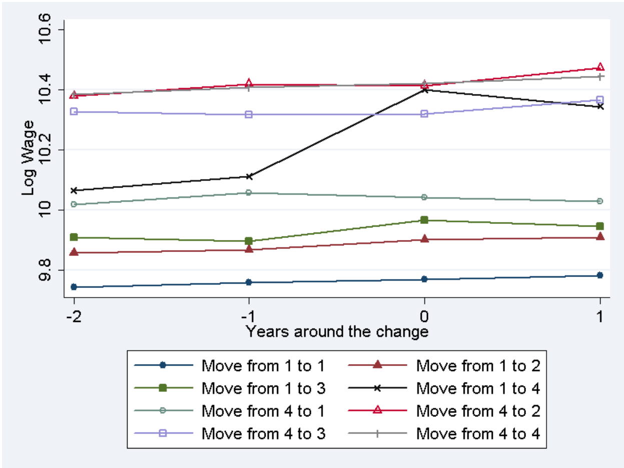

Figure B9: Wage Changes by Wage Quartile (Source: DADS).

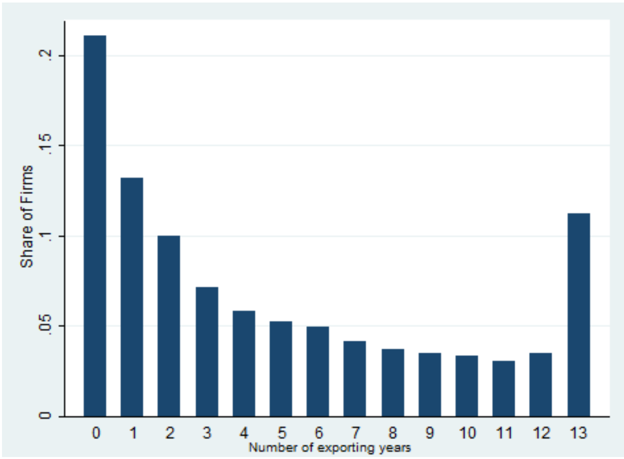

Figure B10: Distribution of Firms by Number of Exporting Years (Source: EAE and Export Customs).

B.6 Additional Tables

Table B1: 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 workers
63	Qualified craft workers
64	Drivers
65	Storage and Transport workers
67	Non-Qualified Industrial workers
68	Non-Qualified craft workers
69	Farm Workers

Table B2: *Non-Exporting Spells*

Number of years exporting	Average spell of non-exporting	Average number in the sample
1	1.63	3.02
2	1.89	4.30
3	1.40	4.89
4	1.19	5.65
5	1.05	6.47
6	0.75	7.06
7	0.75	8.03
8	0.57	8.80
9	0.55	9.72
10	0.45	10.57
11	0.33	11.39
12	0.17	12.17
13	0	13

Notes: Average spells of non-exporting status and number of years in the sample by years of presence in foreign market.

Table B3: Wage Changes when Moving to a New Job

Wage Change	Percentage
Positive	54.82%
Negative	45.18%

Notes: Frequency of positive and negative wage changes for movers.

Table B4: Correlation across proxies of firm types

Deciles of:	VA per worker	Domestic mkt sh	Employment
VA per worker	1	-	-
Domestic mkt sh	0.28	1	-
Employment	0.19	0.59	1

Table B5: Correlation across proxies of worker types

Deciles of:	Lifetime Wage	AKM fixed effects
Lifetime Wage	1	-
AKM fixed effects	0.35	1

Table B6: Pooled Cross-sectional Regressions: Standard Deviation of Worker Type (only current workers)

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Worker Type: Average Lifetime Wage θ^{LW}					
Export	0.020^b	0.010	0.002	-0.003	0.006	-0.014
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)
N.Occ.		0.025^a	0.020^a	0.018^a	0.024^a	0.018^a
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
log empl		-0.032^a			-0.033^a	-0.017^a
		(0.004)			(0.004)	(0.004)
log dom.share			-0.001		$-8.06e^{-5}$	0.001
			(0.001)		(0.001)	(0.001)
log VA per worker				0.040^a	0.041^a	0.080^a
				(0.005)	(0.005)	(0.005)
white share						0.381^a
						(0.013)
log N. Products						0.011^a
						(0.002)
Avg. Lifetime Wage						-0.447^a
						(0.012)
Sector-Year	y	y	y	y	y	y
Obs.	40,579	40,579	40,579	40,579	40,579	40,579
R^2	0.043	0.071	0.066	0.072	0.077	0.253

Export: dummy=1 if firm exports.
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. Lifetime Wage: workers' lifetime wage, averaged by firm.
^{a} significant at 1%, ^{b} significant at 5%, ^{c} significant at 10%.
Notes: Cross-sectional Regressions for firms with more than 5 workers, years 1995-2007. The dependent variable is the dispersion across lifetime wages of workers within a firm. The sample is restricted to the group of workers that do not change firms over their presence in the sample. Different specifications in the columns. Standard errors, clustered at the level of the firm, are reported in parentheses. 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 B7: IV Regressions: *Standard Deviation of Worker Type*, more than 5 workers

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Standard Deviation of Lifetime Wage, more than 5					
	Exp Share$_{t-1}$			Exp Share$_{t-3}$		
	Second Stage					
Export	-0.075^a	-0.081^a	-0.153^a	-0.085^a	-0.092^a	-0.158^a
	(0.019)	(0.020)	(0.035)	(0.022)	(0.027)	(0.057)
	First Stage					
Firm Tariff	0.120^a	0.110^a	0.043^a	0.125^a	0.101^a	0.038^a
	(0.005)	(0.004)	(0.001)	(0.005)	(0.004)	(0.002)
F-stat (First Stage)	528	551	599	668	588	243
Obs.	16,072	16,072	16,072	13,217	13,217	13,217

Firm Tariff: (inverse of) average applied tariff across industry-destination, weighted by the share of firm j exports to each industry-destination the previous period or at $t-3$.
^{a} significant at 1%, ^{b} significant at 5%, ^{c} significant at 10%.
Notes: IV Regressions for firms with more than 5 workers, years 1995-2007. The bottom panel reports the first stage for table 6. Different specifications in the columns. Standard errors, clustered at the level of the firm, are reported in parentheses. 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 B8: Pooled GLS Regressions: Average Worker Type

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Worker Type: AKM Fixed Effects θ^{AKM}					
Export	0.107^a	0.030	0.026	0.035	0.018	-0.004
	(0.025)	(0.024)	(0.024)	(0.024)	(0.025)	(0.028)
N.Occ.		0.007	0.011^a	0.013^a	0.007	0.0057
		(0.005)	(0.003)	(0.003)	(0.005)	(0.005)
log empl		0.028^b			0.021	0.010
		(0.014)			(0.013)	(0.014)
log dom.share			0.012^b		0.005	0.003
			(0.005)		(0.005)	(0.005)
log VA per worker				0.065^a	0.060^a	0.013
				(0.017)	(0.016)	(0.016)
white share						0.404^a
						(0.037)
log N. Products						0.011
						(0.008)
Sector-Year	y	y	y	y	y	y
Obs.	79,689	79,689	79,689	79,689	79,689	79,689
R^2	0.052	0.073	0.073	0.075	0.076	0.089

Export: dummy=1 if firm exports.
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. Lifetime Wage: workers' lifetime wage, averaged by firm.
^{a} significant at 1%, ^{b} significant at 5%, ^{c} significant at 10%.
Notes: Cross-sectional Regressions for firms with more than 5 workers, years 1995-2007. The dependent variable is the within-firm average across worker fixed effects extracted from an AKM regression that includes a quartic in employer-specific experience, time-dummies, a dummy for workers residing in Île-de-France, and time-varying gender effects. Different specifications in the columns. Standard errors, clustered at the level of the firm, are reported in parentheses. 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 B9: Pooled GLS Regressions: Standard Deviation of Worker Types

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Worker Type: AKM Fixed Effects θ^{AKM}					
Export	-0.023^c	-0.026^b	-0.045^a	-0.054^a	-0.034^a	-0.043^a
	(0.012)	(0.013)	(0.013)	(0.013)	(0.013)	(0.014)
N.Occ.		0.022^a	0.011^a	0.010^a	0.021^a	0.021^a
		(0.003)	(0.002)	(0.002)	(0.003)	(0.003)
log empl		-0.048^a			-0.053^a	-0.056^a
		(0.009)			(0.008)	(0.008)
log dom.share			-0.004		0.003	0.003
			(0.003)		(0.002)	(0.002)
log VA per worker				0.032^a	0.035^a	0.023^a
				(0.008)	(0.008)	(0.008)
white share						0.152^a
						(0.020)
log N. Products						0.005
						(0.004)
Avg Worker Type						-0.092^a
						(0.006)
Sector-Year	y	y	y	y	y	y
Obs.	79,689	79,689	79,689	79,689	79,689	79,689
R^2	0.106	0.123	0.115	0.117	0.126	0.158

Export: dummy=1 if firm exports.
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.
^{a} significant at 1%, ^{b} significant at 5%, ^{c} significant at 10%.
Notes: Cross-sectional Regressions for firms with more than 5 workers, years 1995-2007. The dependent variable is the within-firm standard deviation across worker fixed effects extracted from an AKM regression that includes a quartic in employer-specific experience, time-dummies, a dummy for workers residing in Île-de-France, and time-varying gender effects. Different specifications in the columns. Standard errors, clustered at the level of the firm, are reported in parentheses. 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 B10: Pooled Cross-Section Regressions: *Standard Deviation of Worker Type*, more than 5 workers. Weighted standard deviation by worker experience.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Worker Type: Average Lifetime Wage θ^{LW}					
Export	-0.018^{b}	-0.003	-0.019^{b}	-0.031^{a}	-0.007	-0.009
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)
N.Occ		0.022^{a}	0.008^{a}	0.006^{a}	0.021^{a}	0.015^{a}
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
log empl		-0.078^{a}			-0.078^{a}	-0.015^{a}
		(0.004)			(0.005)	(0.004)
log dom.share			-0.005^{a}		0.000	0.001
			(0.001)		(0.001)	(0.001)
log VA per worker				0.042^{a}	0.040^{a}	0.081^{a}
				(0.006)	(0.006)	(0.005)
white share						0.411^{a}
						(0.012)
log N. Products						0.011^{a}
						(0.002)
Avg Lifetime Wage						-0.533^{a}
						(0.010)
Sector-Year	y	y	y	y	y	y
Obs.	57,469	57,469	57,469	57,469	57,469	57,469
R^2	0.056	0.078	0.059	0.062	0.082	0.475

Export: dummy=1 if firm exports.
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. Lifetime Wage: workers' lifetime wage, averaged by firm.
^{a} significant at 1%, ^{b} significant at 5%, ^{c} significant at 10%.
Notes: Cross-Sectional Regressions for firms with more than 5 workers, years 1995-2007. The dependent variable is the weighted dispersion across lifetime wages of workers within a firm, with in-firm worker experience as weights. Different specifications in the columns. Standard errors, clustered at the level of the firm, are reported in parentheses. 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 B11: Pooled Cross-Section Regressions: *Average Worker Type*, more than 5 workers. Lifetime wage conditioned on experience.

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Worker Type: Average Lifetime Wage θ^{LW}					
Export	0.076^a	0.024^b	0.021^c	0.024^b	0.006	0.023^c
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.014)
N.Occ		0.016^a	0.024^a	0.023^a	0.012^a	-0.006^a
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
log empl		0.056^a			0.058^a	0.069^a
		(0.007)			(0.007)	(0.006)
log dom.share			0.015^a		0.000	0.000
			(0.002)		(0.002)	(0.002)
log VA per worker				0.153^a	0.154^a	0.078^a
				(0.009)	(0.009)	(0.008)
white share						0.687^a
						(0.020)
log N. Products						-0.006^c
						(0.004)
Sector-Year	y	y	y	y	y	y
Obs. Observations	56,906	56,906	56,906	56,906	56,906	56,906
R^2 R-squared	0.142	0.164	0.162	0.183	0.188	0.277

Export: dummy=1 if firm exports.
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.
[a] significant at 1%, [b] significant at 5%, [c] significant at 10%.
Notes: Cross-Sectional Regressions for firms with more than 5 workers, years 1995-2007. The dependent variable is the average lifetime wage of workers within a firm, after controlling for the average worker experience. Different specifications in the columns. Standard errors, clustered at the level of the firm, are reported in parentheses. 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 B12: Pooled Cross-Section Regressions: *Standard Deviation of Worker Type*, more than 5 workers. Lifetime wage conditioned on experience.

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Worker Type: Average Lifetime Wage θ^{LW}					
Export	0.003	0.000	-0.013	-0.019^b	-0.004	-0.021^b
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
N.Occ		0.026^a	0.017^a	0.016^a	0.026^a	0.019^a
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
log empl		-0.055^a			-0.056^a	-0.029^a
		(0.004)			(0.005)	(0.004)
log dom.share			-0.003^c		0.002	0.001
			(0.001)		(0.001)	(0.001)
log VA per worker				0.024^a	0.022^a	0.041^a
				(0.006)	(0.006)	(0.005)
white share						0.399^a
						(0.0122)
log N. Products						0.010^a
						(0.002)
Avg Lifetime Wage						-0.420^a
						(0.007)
Sector-Year	y	y	y	y	y	y
Obs. Observations	56,906	56,906	56,906	56,906	56,906	56,906
R^2 R-squared	0.052	0.070	0.062	0.063	0.071	0.322

Export: dummy=1 if firm exports.
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. Lifetime Wage: workers' lifetime wage, averaged by firm.
^{a} significant at 1%, ^{b} significant at 5%, ^{c} significant at 10%.
Notes: Cross-Sectional Regressions for firms with more than 5 workers, years 1995-2007. The dependent variable is the dispersion across lifetime wages of workers within a firm, after controlling for the average worker experience. Different specifications in the columns. Standard errors, clustered at the level of the firm, are reported in parentheses. 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 B13: Pooled Cross-Section Regressions: *Standard Deviation of Worker Type*, more than 5 workers, AKM decomposition with match fixed effects.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
	Worker Type: AKM fixed effects θ^{AKM}					
Export	-0.026^a	-0.013	-0.031^a	-0.045^a	-0.017^c	-0.035^a
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.012)
N.Occ.		0.031^a	0.015^a	0.013^a	0.030^a	0.026^a
		(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
log empl		-0.094^a			-0.093^a	-0.089^a
		(0.005)			(0.005)	(0.005)
log dom.share			-0.007^a		-0.000	-0.001
			(0.002)		(0.001)	(0.002)
log VA per worker				0.039^a	0.038^a	0.026^a
				(0.006)	(0.006)	(0.006)
white share						0.150^a
						(0.016)
log N. Products						0.010^a
						(0.003)
Avg. Lifetime Wage						-0.086^a
						(0.005)
Sector-Year	y	y	y	y	y	y
Obs.	56,815	56,815	56,815	56,815	56,815	56,815
R^2	0.057	0.080	0.063	0.064	0.082	0.115

Export: dummy=1 if firm exports.
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. Lifetime Wage: workers' lifetime wage, averaged by firm.
^{a} significant at 1%, ^{b} significant at 5%, ^{c} significant at 10%.
Notes: Cross-Sectional Regressions for firms with more than 5 workers, years 1995-2007. The dependent variable is the within-firm standard deviation across worker fixed effects extracted from an AKM regression that includes a quartic in employer-specific experience, time-dummies, a dummy for workers residing in Île-de-France, time-varying gender effects, and match effects. Different specifications in the columns. Standard errors, clustered at the level of the firm, are reported in parentheses. 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 B14: Sectoral Rank Correlations, GLS Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables				Rank Correlation			
Export	0.037^a	0.033^a	0.018^b	0.024^a	0.035^a	0.011	0.022^b
	(0.009)	(0.009)	(0.009)	(0.009)	(0.011)	(0.007)	(0.011)
log empl		0.002		-0.004	-0.001		-0.008
		(0.004)		(0.004)	(0.007)		(0.007)
log VA per worker			0.074^a	0.078^a		0.096^a	0.100^a
			(0.014)	(0.015)		(0.020)	(0.021)
Sector,Year	y[1]	y[1]	y[1]	y[1]	y[2]	y[2]	y[2]
Obs.	3,812	3,812	3,812	3,812	3,812	3,812	3,812
R^2	0.082	0.082	0.094	0.094	0.333	0.343	0.343

[1] 2-digit sector dummies.
[2] 4-digit sector dummies.
log empl: average log-employment.
log VA per worker: average log-value added per worker.
[a] significant at 1%, [b] significant at 5%, [c] significant at 10%.
Notes: Industry regressions, years 1995-2007. Different specifications in the columns. Standard errors, clustered at the sector-level, are reported in parentheses.