The characteristics of worker flows by firm growth: empirical evidence from a matched firm-worker dataset from France

Matthieu Bellon*

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Abstract

This paper investigates the effects of firm growth on hiring and separations and contributes to the literature on worker flows by studying the wages and characteristics of new and separated workers. First, I show that separations are an essential and robust component of firm growth. I argue that this may be the result of a more intense search for better matches at faster growing firms. Second, I find that wage offers to new hires increase with firm hiring rates. This is partly the result of the selection of more experienced workers. However fixed unobservable and variable observable worker characteristics cannot fully explain this relationship: the residual wage of new hires is significantly associated with the firm hiring rate. We interpret this as direct evidence of the firm-level upward-sloping labor supply curve predicted by the canonical models. We provide estimates of the slope of the curve using an instrumental variable approach to control for supply shocks. We find that a 10% increase in the hiring rate results in a wage increase of 1%.

1 Introduction

A vast literature has established that labor markets around the world are characterized by large flows of workers in and out firms, and in excess of firm job creations and destructions.[1] A lot of attention has been devoted to variations in the magnitude of worker flows with firm growth, and a lot less to the variations in the characteristics and wages of new and separated

*PhD candidate, Department of Economics, Columbia University; address: 1022 International Affairs Building, Mail code 3308, New York, 10027; email: mb3413@columbia.edu; telephone: 917-331-5847

[1]See Bassanini and Marianna (2009) [6] for a survey about job and worker flows in OECD countries.

workers. In fact, in one of the seminal studies of worker flows, Abowd et al. (1999) [1] conclude that "to complement [their] analysis, one should consider the wage patterns for entering and exiting workers". Surprisingly, no study has yet undertaken to address this question in a comprehensive way.

In parallel with the empirical work on worker flows in and out firms, the new canonical models[2] of labor have focused on firm-worker interactions with frictions. These models predict the existence of an upward-slopping labor supply curve at the firm level: all else being equal, firms that hire more workers have to offer higher wages.[3] In this context, the overlooked but robust fact that growing firms separate with more workers is puzzling.[4] Furthermore, the existence and measurement of a firm-level upward-sloping labor supply curve in the data has received little attention,[5] which is surprising given the robustness of the prediction across models.

This paper uses a comprehensive matched firm-worker dataset from France to examine these issues and extend the study of how worker flows and wage offers vary with firm growth. The dataset is constructed from three censuses in order to obtain complete information on firm characteristics, worker flows, and on the wages and characteristics of new, separated and continued workers, making it well suited for the analysis. Specifically, the richness of the dataset allows me to complement the empirical literature in three ways. First, I characterize the relationship between the separation and the growth rates at the firm level. Second, I document the systematic relationships between characteristics of new and separated workers and firm growth. Third, I test for the existence of an upward-sloping labor supply at the firm level and use an instrumental variable approach to estimate its slope.

The first results demonstrate that separations are an essential component of firm growth.

[2]Among the most prominent of them are the model developed by the 2010 Nobel prize winners Peter Diamond, Dale Mortensen and Christopher Pissarides. See Rogerson et al. (2005) [36] and Cahuc (2014) [15] for reviews.

[3]Leading models include Burdett and Mortensen (1998), [13] Shimer (2005), [39] Kaas and Kircher (2015) [26] and Bellon (2016) [7] also features the same prediction.

[4]See Davis et al. (2012) [20] for the U.S., and Duhautois and Petit (2015) [22] for France.

[5]The work of Schmieder (2013) [38] on start-up establishments is a notable exception.

The positive association between firm positive growth rates and separation rates holds for different short- and long-term growth measures, and remains significant after controlling for firm variable and fixed effects. It indicates that *when* a firm grows faster by 10%, the separation rate simultaneously increases by 1.2%. The findings mean that faster growing firms separate with more incumbent workers or recruit workers that are more likely to leave soon after. The data provides ambiguous answers about which of these effects dominate. On one hand, I find that the tenure of both new and leaving workers increase with the growth rate. On the other hand, the number of separations of workers hired the previous year or before does not increase with firm growth.

Second, I find that wages and worker characteristics vary systematically with firm positive and negative growth rates. The wage of new and separated workers increase substantially with firm shrinking rates. This pattern goes along with the positive association of average labor market experience of new and separated workers with shrinking rates. For separated workers, this is likely the effect of French regulations that require firms to separate with younger and junior workers first in the case of economic lay-offs. In addition, the job spell of new hires at declining firms decreases sharply with shrinking rates, suggesting that the observed higher wage offers may compensate for the higher risk of future lay-offs.

I find that the wages of new hires are lower than the wages of incumbents, but that wage offers increase with firm hiring rates. The bulk of the average wage differential can be explained by observable characteristics as faster growing firms hire more experienced workers that were more often already employed at other firms. However, when the hiring rate increases, there is an increase in wages that cannot be explained by changes in the composition of new hires. This is direct evidence of the upward-sloping labor supply curve predicted by canonical models. I show that the effect of the hiring rate on the wage of new hires persists over the job spell and does not vanish when controlling for worker fixed effects. By contrast, the wage and characteristics of separated workers at growing firms are mostly unrelated to firm growth.

Third, I estimate the slope of the labor supply curve faced by individual firms. To do so, I use an instrumental variable approach that borrows from Hummels et al. (2014) [25] in order to deal with the endogeneity of firm hiring rates. The instrument only applies to exporters and therefore I then restrict the analysis to these firms. The instrument interacts the initial export structure of firms with variations in product demand from foreign countries. I find that the instrument is valid and corrects for the expected bias that would result from labor supply shocks. The IV estimates imply that the wage of new hires increase by 1% when the firm hiring rate increases by 10%.

This paper is related to three different strands of the empirical labor literature. Starting with Abowd et al. (1999) [1] for France and Burgess et al. (2001) [14] for the U.S., empirical studies on the variation in worker flows with firm growth have demonstrated that, essentially, firms grow by increasing their hiring rate and shrink by increasing their separation rate. The findings were later extended by Davis et al. (2006, [19] 2012, [20] and 2013 [21]) who showed that firm adjustments tend to be lumpy, that the share of separations resulting from lay-offs increases with the shrinking rate, and that the hiring rate at growing firms increases faster that the vacancy rate. Duhautois and Petit (2015) [22] show that hiring and separation patterns in France are very similar to those in the U.S.

Few papers consider the link between firm growth and the changes in wages and worker characteristics. Noteworthy exceptions include the work of Caliendo et al. (2015) [17] who study the organization of firms in hierarchical layers of occupations in France. They find that the number and characteristics of occupation layers vary with firm growth, be it through internal reorganization, hiring or separations.[6] This paper however does not directly look at the characteristics of new and separated workers. Therefore the closest work related to mine is Schmieder (2013). [38] The author uses German data to show that new establishments pay higher wages and argues that it is because of their significantly higher growth. He proceeds

[6] In particular they focus on changes in the average characteristics of existing layers, showing that wages and measures of knowledge decrease at existing layers when firm grow by adding a layer and increases when firm grow without doing so.

with the estimation of the slope of the labor supply curve of new establishments using their age as an instrument. The focus on small start-up establishments makes it complementary to the present study on large exporting firms. The findings are nevertheless coherent.

This paper also relates to a recent literature on the firm employment effects of international trade. Using French data, Biscourp and Kramarz (2007) [10] and Kramarz (2008, [27] 2011) [28] find that increases in import and export of final goods are associated with decreases in employment while imports of intermediates are associated with employment growth[7]. Despite these empirical facts, I find that increases in demand from foreign trade partners are good predictors of hiring. Hummels et al. (2014) [25] also successfully use the same type of instrument with Danish data to show that firm export growth causes an increase in the average wage of workers. They also find that imports of the final goods that are similar to those produced by a firm (offshoring) cause an increase in the firm average wage of high-skill workers and a decrease in the average wage of low-skilled. Krisha et al. (2011 [29] and 2014 [31]) use a linked firm-worker database from Brazil to evaluate the wage effects of trade. They argue that the firm average wage increase resulting from more exports only stems from the hiring of better workers and the selection of better matches.

The rest of the paper is organized as follows. In the next section, I present the data sources and how I construct the datasets used in the analysis. In section 3, I present the first descriptive statistics and examine the relationships between worker flows and job growth rates. In section 4, I document how changes in firm growth is related to variations in the wages and characteristics of new and separated workers. In section 5, I use an instrumental variable approach to estimate the slope of the labor supply curve for individual firms. Section 6 concludes.

[7]Kramarz (2008) [27] additionally argues that increases in imports of final goods (offshoring) and its employment effects are more prevalent at firms that face stronger unions.

2 Firm level data on jobs, worker careers and trade

This section provides an overview of our data sources and the main features the construction of datasets, including data definitions and the matching of firm variables across datasets.

2.1 Institutional background

The analysis cover the period from 1995 to 2007. Despite some significant events including the Chinese accession to the World Trade Organization in 2001, the introduction of the euro in 1999, and the ongoing process of the European integration,[8] macroeconomic conditions were remarkably stable over the period. The GDP growth rate fluctuated between 1% and 4% throughout the period. Also during the period, a set of labor market reforms to payroll taxes reduced the labor costs of employing low-skilled workers in order to counteract the many increases in the minimum wage (Askenazy (2013) [3]). I use the wage inclusive of labor taxes in the analysis in order to focus on labor costs and the determinants of firm decisions with respect to employment.

While the French labor market is heavily regulated,[9] recent reforms and the existence of fixed term contracts (FTC) effectively grant firms some substantial flexibility. As noted in Abowd et al. (1999), [1] firms can make substantial employment adjustments without violating French regulations limiting firms' ability to lay-off workers by increasing or reducing hires on FTC and adjusting their lengths.[10] Unfortunately, the data that I use do not contain information on the type of contracts but Duhautois and Petit (2015) [22] show that patterns of hiring and separations by firm growth are very similar for both FTC and open-ended contracts (OEC). Moreover, firms are allowed to lay-off OEC workers for economic reasons. When they choose to do so, they must guarantee an equal treatment of employees by laying-

[8]In particular, eight countries from Eastern Europe, Cyprus and Malta joined the European Union in 2004 following a long multi-step integration process.

[9]See Botero et al. (2004) [12] for international comparisons of employment protection laws.

[10]FTC represent approximately 3 hires out of 4 and two-thirds of separations. However, the share of FTC in total employment has been consistently estimated to be approximately 9% since the end of the 1990s.

off workers according to a set of criteria set by law. Workers with higher seniority in the firm, family responsibilities, special needs, or that are less likely to find another job (because of age for example) must be laid-off last. As regards wage setting, a series of laws at the end of the 80's and in the 90's relaxed the regulations on wage negotiation to grant more flexibility to firm for setting wages. By 2005, according to Carlier and Naboulet (2007),[18] 41% of the workers employed in private firms with more than 10 employees were covered by a firm-level wage agreement signed that very same year.

2.2 Data sources

This subsection gives an overview of the four sources that I draw from and their use in the analysis. The four sources allow me to collect data for the years 1995-2007 on jobs and on manufacturing firms in France, on the international trade of French firms, and on world trade. Technical details about coverage, data construction including the merging of datasets, and the exclusion of unreliable observations are presented in appendix (section A).

First, I obtain data on jobs from the *Déclarations Annuelles de Données Sociales* (henceforth the DADS) which consist of the mandatory firm reports of the earnings of workers to government agencies. From these reports, the French National Institute of Statistics and Economics Studies (henceforth the INSEE) puts together two DADS datasets that I use in the study. In both datasets the unit of observation by year is the job, defined as a worker-firm pair, and the variables provide the gender, age, and residence of workers as well as the earnings, hours, occupation category and full or part time status of jobs. However the datasets differ in their structure and coverage.

The DADS-Panel dataset provides detailed information on all the jobs in the private sectors of the workers born in October in odd years. The dataset has the features of traditional matched employer-employee data: there are firm and worker identifiers that allow for the construction of a firm-worker panel.

By contrast, the DADS-Postes dataset covers the universe of jobs in private sector firms for all workers. However, this dataset does not have worker identifiers. Instead, the data is organized in overlapping two-year panels of jobs. For every observation in the panel covering the years $t-1$ and t, the set of variables provides information about job characteristics in $t-1$ and/or in t depending on whether the job exists in either year or in both. This specific panel structure and the existence of a firm identifier allows me to construct variables that characterize the flow of workers in and out firms before I aggregate data at the firm level.

The different natures of these datasets make them suitable for different purposes. I use DADS-Panel the matched employer-employee data to control for firm and worker unobservable fixed effects and to obtain information about job spells. I use DADS-Postes the census of private sector jobs to construct accurate measures of worker flows at the firm level.

I obtain information on firms characteristics from the *Enquête Annuelle d'Entreprise* (henceforth the EAE), the census of manufacturing firms of 20 employees and over conducted by the INSEE because the DADS datasets have little information about firms. This allows me to complement workforce variables with annual firm characteristics including revenues, value added, inputs, capital, and investment. Throughout the study, I restrict the analysis to the manufacturing firms in the EAE because these are the only firms for which I can control for typical firm variables including revenues and capital intensity.

I supplement the information on firms from the EAE with annual firm-level customs data from the *données import/export du commerce extérieur* (henceforth, the customs data) that are collected by the *Direction Générale des Douanes et des Droits Indirects*. Thereby I get the quantities and values of imports and exports by product category and destination for every French firm. The data cover the universe of international transactions with countries that are not members of the European customs union and all the transactions with union members that are above a specific threshold.[11]

I also get trade data between countries by product category from the *Base pour l'Analyse du Commerce International* (henceforth BACI) developed by the CEPII[24] and based on

[11] See section A.4 in appendix for more details.

the United Nations Statistics Division's COMTRADE database. In both trade datasets, the product categories are from the six-digit Harmonized System classification (henceforth HS6). The French customs data together with BACI allow me to construct the firm level index of foreign demand that is used in the empirical instrumental variable approach.

2.3 Data construction

I combine the information from the above sources to construct two datasets, namely EAE-Trade-Postes and EAE-Trade Panel. Specifically I use the administrative firm identifiers SIREN (the *Système Informatique du Répertoire des ENtreprises* code) present in all sources to match observations at the firm level. For both datasets I start with the manufacturing firms in the EAE, I import the firm trade variables and the firm level index of foreign demand. Then, I respectively import aggregated job data at the firm level from DADS-Postes and job-level data from DADS-Panel to construct the two datasets. Despite the fact that the firm identifier SIREN is a national code used for many administrative purpose, the matching is far from perfect, in particular because of frequent changes in SIREN codes resulting from reorganizations and because conglomerates change how they allocate their revenues, workers and assets across their firms in their reports.

The constructed EAE-Trade-Postes is a coherent sample of the initial manufacturing-firm-level EAE dataset about balance sheets, with additional information on workforce characteristics, worker flows and firm trade. To construct EAE-Trade-Postes, I started with a database of matched observations from EAE and DADS- Postes that account for 95% of the observations in the initial EAE dataset. Then I excluded outliers and inconsistent values and kept 61% of the observations in the matched database. To summarize, I excluded from the analysis the observations for which the values from different sources were inconsistent, the observations corresponding to the first and last year of firm appearance in the 1994-2008 DADS datasets, the observations with outlying values for the job growth rate, and the firms that belong to a handful of problematic conglomerates.[12] I also exclude the firm-year observations for which the reported number of establishments changes. This selection is implemented to rule out the worker flows resulting from the sale and acquisition of establishments which are out of the scope of the present analysis. Finally, the EAE-Trade-Postes dataset includes 33,897 of the 39,880 firms present in the initial EAE dataset, and all their workers.

EAE-Trade-Panel is a worker-level matched firm-worker dataset with the workers that worked at least once at a firm present in the EAE. In addition to individual worker variables, EAE-Trade-Panel has the firm-level information imported from EAE-Trade-Postes. I follow Woodcock (2007) [40] and restrict the sample of workers by selecting the firms that have a minimum of five sampled workers and that also belong to the largest connected group in the sense defined in Abowd et al. (1999). [2][13] The dataset follows 248,813 workers across 16,843 firms, including 11,457 firms that are also present in the EAE-Trade-Postes sample.[14]

2.4 Characterizing the workforce and worker flows

In this subsection, I describe the construction of the variables that I use to measure worker flows and worker characteristics at the firm level. First, I use the job-level observations in the DADS to identify new and terminated jobs. Second, I build on this analysis to construct a measure of the worker flows in and out firms. Third, I define averages characterizing new hires, workers that leave their firm and the other workers. More details about the definition of these variables can be found in sections A.1 and A.2 in appendix.

First, I define new hires as the workers that are not observed at the firm in the previous year. In DADS-Postes, there is an indicator that differentiate "principal" jobs from "side"

[12] See section A.7.2 in appendix for more details about this step.

[13] Connected groups are groups of firms that are linked to one another by switching workers. See section A.8 in appendix for more details about this step.

[14] I report separately the sample averages for the EAE-Trade-Postes and EAE-Trade-Panel in table 11 of the appendix. because I only kept firms with at least five sampled workers, the firms in the EAE-Trade-Panel are on average larger, more productive, more engaged in international trade. They pay higher wages and experience smaller worker flows.

jobs with low earnings or low ratio of hours worked per day. Specifically I only count as new hires the workers in "principal" jobs that did not have a principal job at the same firms the year before. Similarly I define terminated jobs as the workers in principal jobs that do not have a principal jobs at the same firms in the following year.

Second, I use EAE-Trade-Postes to compute the average number of jobs and worker flows at a firm for every year. The total number of different workers employed during the year is not suited to characterize the size of firm workforces because of replacements. I formally define replacements as the minimum between the number of new hires and leaving workers. Then I define the number of jobs in a year as the difference between the total number of different workers minus replacements. The number of jobs is not appropriate to characterize the average employment of fast-changing firms as it overestimates the workforce available at fast-growing firms and underestimate the workforce at fast-declining firms. Therefore I define the initial number of jobs as the number of jobs before the net change in the number of workers over the year. Finally the average number of jobs in a year is the average between the initial number of jobs and the number of jobs.

The hiring rate is defined as the ratio of new hires to the average number of jobs while the separation rates is the number of terminated jobs to the average number of jobs. The job growth rate is the difference between these two, or equivalently, the ratio of the net change in the number of workers during the year to the average number of jobs.

Third, I compute firm averages for new and not-new jobs, terminated and continued jobs. For every job category, I compute the share of hours worked by female workers, by workers at part-time jobs, and by workers in each of five occupation groups.[15] I also compute by job category the weighted average of labor market experience[16] and the weighted average of log hourly wages, where I use hours worked as individual weights.

The construction of these variables are implemented in both EAE-Trade-Postes and EAE-

[15]These five occupation groups correspond to firm directors, senior staff, supervisors, clerical workers and blue collar workers. See footnote 38 for more details.

[16]I define labor market experience as age minus 18.

Trade-Panel. Because the latter dataset only contains a subsample of all workers, the averages computed on the sampled workers are proxies for the actual workforce averages. However, the nature of EAE-Trade-Panel allows for the definition of an additional job category and the computation of two new variables. First, I classify job changes as job-to-job transitions when the time between the end date of the terminated jobs and the start date of the new job is less or equal than 15 days.[17] Then, I define the share of hours worked by job switchers among new hires and leaving workers. Finally, I also compute the weighted average of the tenure of leaving workers and the weighted average of the future job spell of new hires.[18]

3 Firm growth and worker flows

In this section, I present salient features of firm-level worker flows in the French labor market. In particular, I focus on the differences between declining, stable and growing firms in terms of hiring and separations.

3.1 Descriptive statistics and first stylized facts

The average characteristics of the EAE-Trade-Postes sample are reported in table 8 in appendix and table 1 below features the part pertaining to worker flows. Averages for the entire selection of firms are displayed in the first column of the tables. Despite the focus on manufacturing firms, the annual hiring and separation rates of 20.5% and 19.8% are consistent with the numbers reported in Duhautois and Petit (2015) [22] using a census of French establishments of 50+ workers for 1999-2010, and with the numbers in David et al. (2012) [20] for U.S. establishments in the 2000's. In addition, the data allows us to look at the average wage of transitioning workers. The hourly wage of separated workers is the same

[17]In doing so, I follow the definition used in Postel-Vinay and Robin (2002). [35]

[18]Because I can only observe jobs until the end of the sample period, this variable is obviously censored from the top. In the regression analysis, I control for the censoring with cohort effects.

Table 1: Worker flow characteristics by growth status in EAE-Trade-Postes.

	All firms		Firm growth status: Declining		Stable		Growing	
number of firms	33 897							
number of observations	209 264		92 911		22 545		93 808	
DADS-POSTES variables:								
number of workers	111,6	(299,9)	125	(352,7)	48,7	(64,1)	113,5	(274,5)
hiring rate	20,5	(17,2)	13,5	(12,5)	16,7	(14,0)	28,4	(18,6)
separation rate	19,8	(14,4)	22,2	(14,4)	16,6	(13,6)	18,2	(14,3)
average wage (1000€.p.w)	20,5	(5,7)	20,5	(5,6)	21,0	(5,8)	20,3	(5,7)
hourly wage	12,7	(3,3)	12,7	(3,3)	12,7	(3,4)	12,7	(3,3)
hourly wage of new hires	10,8	(4,0)	11,1	(4,4)	10,4	(4,1)	10,6	(3,7)
hourly wage of separated	12,7	(5,2)	13,1	(5,2)	12,3	(5,4)	12,3	(5,2)

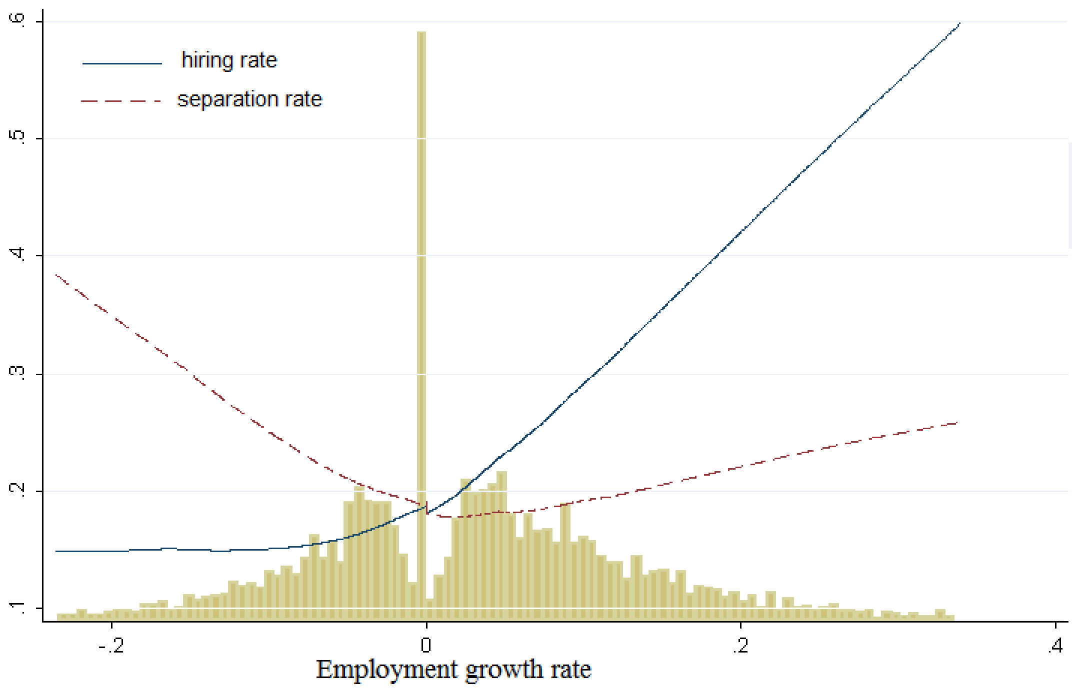
Sources: DADS-Postes, customs data and EAE 1995-2007. The variable definitions are presented in the relevant subsections of the data appendix (section A). Standard deviations are in brackets. In a preliminary step, all ratio variables were winzored at the 1% level.

as for all workers. By contrast, the hourly wage of new hires is 15% lower.

I partition the observations in three groups depending on whether the firm growth rate in the average number of jobs is negative, null or positive. The average characteristics for the corresponding groups of growing, stable and declining firms are then reported in the third, fifth and seventh columns of tables 8 and 1. The growth rate is given by the difference between the hiring and separation rates by construction. I compare declining and growing firms to stable ones. Declining firms reduce their workforce by 8.7% on average and the reduction is achieved both by separating with more workers and by hiring less new workers. By contrast, growing firms grow at an average rate of 10.2% despite a larger separation rate of 18.2% instead of 16.6% for stable firms. These differences could come from a composition effect as stable firms tend to be smaller.

I examine the relationship between the growth rate of jobs and worker flows in more details with the help of figure 1. The figure features two non-parametric bi-variate regressions between the growth rate in the average number of jobs and the hiring and separation rates respectively. The findings are consistent with the results in Duhautois and Petit (2015) [22] and David et al. (2012). [20] The graph reveals that the hiring rate monotonically increases with the growth rate of the number jobs. The relationship between the separation rate and the job growth rate has an inverted U-shape and confirms that faster growth is associated with more worker separations.

Figure 1: Worker flows and job growth rates.



Source: EAE-Trade-Postes 2000. The histogram corresponds to the distribution of the average number of job growth rates as defined in subsection 2.4. The lines correspond to separate non-parametric bi-variate regressions of the hiring and separation rates on job growth rates. 1% of the job growth growth rates were trimmed at both ends of the distribution.

There is no substantial difference in table 1 between the average hourly wages of the different firm groups. The relative difference between the wage of new and separated workers is also similar across firm groups. By contrast, there are some significant differences for transitioning workers: the hourly wage of new and separated workers is higher at declining firms.

However the presence of notable differences in other firm characteristics prevent us to draw any conclusions at this stage. In particular, the upper part of table 8 in appendix reveals that declining firms tend to have more revenues, more workers, and more capital per worker despite a higher value-added per worker ratio compared with growing firms. They engage more and more often in international trade. The difference in the composition of firms is certainly mirrored by difference in the composition of workers across groups; the next sections investigate the role of composition effects.

3.2 Pervasiveness of the separations-growth rate relationship

At this point, there could be several candidate explanations for the positive association between the separation rate and the increase in the number of jobs:

(i) This pattern could be the result of a composition effect if firms with more separations (because of inherent intense turnover for example) are more volatile. In this case, volatility in the job growth rate at firms with high turnover would have them be disproportionately represented among fast-growing firms, thereby driving a positive relationship between separations and growth.

(ii) Alternatively the pattern could result from temporary labor supply shocks. Consider the case of a positive shock where it is suddenly possible for a firm to hire a group of workers with better ability and/or at a lower wage than its incumbent workers. In the absence of growth perspective, the firm would want to replace its incumbent workers with these newly available workers without increasing the size of its workforce. It would hire these workers immediately but slowly separate with its incumbent workers because of labor protection regulation. This would then result in a temporary growth in the number of jobs together with an increase in the separation rate.

(iii) Matches created when firms are growing faster may be systematically less successful and end up more often into separations

(iv) Long term expansions may be systematically associated with changes in the composition of the workforce requiring growing firms to separate with incumbent workers.

In this subsection I test for these hypotheses and examine the extent of the separation rate-growth rate relationship.

The empirical approach is based on equation (1) where the separation rates (sr) of firms indexed by j in years indexed by t are related to measures of growth (gr). I use different alternative measures of growth to assess the robustness and test the candidate explanations of the pattern. For all measures however, I split the growth rate in two variables, $(\min\{\mathsf{gr}, 0\}, \max\{0, \mathsf{gr}\})$, in order to consider positive and negative growth separately. The variables are never non-zero at the same time. The first variable is only non-zero for negative rates and therefore captures the relationship between the separation rate and the growth rate for declining firms. The opposite is true for the second variable and growing firms.

$$\mathsf{sr}_{j,t} = \beta_{min} \min\{\mathsf{gr}_{j,t}, 0\} + \beta_{max} \max\{0, \mathsf{gr}_{j,t}\} + \alpha.X_{j,t} + \epsilon_{j,t} \tag{1}$$

The set of firm level controls included in $X_{j,t}$ vary with the different specifications.

The estimation results are reported in table 2. The specification in the first column correspond to equation (1) without controls[19]. It confirms the findings of the previous section showing that separation rates increase with shrinking and growing rates.

Starting with the second column, firm fixed effects, controls and weights are introduced in the specifications.[20] Controls include characteristics of the workforce such as the average log hourly wage and labor market experience of incumbent workers, the share of hours worked by by occupation category, by part-time workers, and by female workers. I also include the logarithm of revenues, material expenditure, exports and imports as well as the investment rate and a dummy for exporters and importers.

From now on with firm effects, the identification relies on variations in growth rates within firms. I can test for the relevance of the candidate explanation (i) by comparing the estimates in the first and second columns. The coefficient estimate of positive growth rate in the second column is substantially lower, meaning that firms characterized by higher separation rates have large positive growth rates more often. However the estimate is still positive and significant, meaning that firms separates with more workers *when* they grow faster. In appendix, I also verify that this result holds on the subsample of single-establishment firms. Hence the candidate explanation (i) alone cannot explain the pattern.

[19] In this respect, estimates of the first column correspond to the slopes of figure 1.

[20] They are introduced sequentially in the table 13 in appendix. The results show that most of the difference with the first column comes from the firm effects.

Table 2: The relationship between separation rates and firm growth: an overview.

Dependent variable: the separation rate	(13.A) Basic	(13.C) FE, Weights & controls	(13.E) Revenue growth	(13.F) Smoothed growth	(14.B) Panel proxy	(14.C) Panel non-hire separations
max(0,growth rate)	0.394***	0.122***	0.033***	0.081***	0.087***	-0.009
	(0.008)	(0.009)	(0.004)	(0.007)	(0.014)	(0.010)
min(growth rate,0)	-0.992***	-0.839***	-0.072***	-0.563***	-0.534***	-0.535***
	(0.006)	(0.007)	(0.008)	(0.019)	(0.023)	(0.021)
Firm effects	NO	YES	YES	YES	YES	YES
Controls	NO	YES	YES	YES	YES	YES
Weights	NO	Njob	Njob	Njob	Njob	Njob
Observations	209,264	187,896	189,132	187,896	44,318	44,318
R-squared	0.179	0.691	0.563	0.588	0.534	0.431

Sources: EAE-Trade-Postes for columns 13.A-F and EAE-Trade-Panel for columns 14.B-C. Complete tables including estimates of controls and more details about the specifications are in tables 13 and 14 in appendix. In column 13.A, estimates are from a simple OLS regression without controls. Firms effects, weights and controls are included in all the other columns. Revenue growth is used instead of job growth in 13.E. A three year moving average of the growth rate in the average number of jobs is used in 13.F. In 14.B, the separation rate used is the EAE-Trade-Panel proxy. In 14.C, the separation rate is computed as the ratio of separations of non-new hires to the average number of jobs. Firm-level clustered standard errors are in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

What are the results for the hiring rate? The coefficient estimates can easily be deducted for specifications 13.A-C. In this case the growth rate refers to the growth in the average number of jobs which is the sum of the hiring and separation rates ($\mathsf{jgr} = \mathsf{hr} - \mathsf{sr}$). Therefore the coefficient estimate of the effect of growth on the hiring rate is equal to the estimate of the effect on the separation rate plus one.[21] It follows that growing firms hire more workers than the net increase in their number of workers.

In columns 13.E-F, I use alternative measures of firm growth rate to assess whether more separations at growing firms are the result of temporary labor shocks (candidate explanation (ii)). Specifically I use the growth rate of revenues and a three-year moving average of the growth rate in the number of jobs. The coefficient estimate of the positive growth rate remains highly significant. This rules out candidate (ii) as the main explanation of the pattern.

[21] Respectively 1.394 and 1.122 for the positive growth rate in specifications (13.A) and (13.C). Respectively .008 and .161 for the negative growth rate in specifications (13.A) and (13.C).

The last columns of table 2 aims at discriminating between the candidate explanations (iii) and (iv). To do so I use the EAE-Trade-Panel dataset constructed from a true panel of workers. This allows me to distinguish the separation of recent hires from the separation of workers that were already employed at the firm the year before. The limited panel structure of EAE-Trade-Postes prevented this distinction. The caveat of using EAE-Trade-Panel is that I can only compute proxies, namely the separation rates among the subsample of workers born in October of odd years. I verify in column 14.B that the positive association between separations and growth is still significant using proxies.[22] I then consider the effect on the separation rate of non-recent hires. The coefficient estimate is not statistically different from zero. This points to candidate (iii) as a better explanation than candidate (iv), indicating that matches created when firms grow faster are less successful.

4 Firm growth and the wages of new and separated workers

This subsection focuses on the comparison of characteristics and wages between new, separated and continued incumbent workers at firms with different growth rates.

4.1 Wage differentials and observable differences in the characteristics of new and separated workers

I showed in the previous section that the wage of new hires was substantially lower compared with incumbents. Can the characteristics of new workers explain the difference in wages? I compute the average characteristics by job category (new, separated or continued) in table 3. Indeed, the composition of transitioning workers, new or separated, differ from

[22] There are actually two differences between columns 13.C and 14.B. The first difference is the use of a proxy for the separation rates. The second difference is that EAE-Trade-Panel only includes a subsample of the firms EAE-Trade-Postes. In column 14.A, I verify that the coefficient estimate obtained using the same true separation rates on the EAE-Trade-Panel subsample is not statistically different from the ones obtained on the full sample.

the rest of workers. New hires are more likely to work part-time. New and separated workers have less experience[23] and are more often women.

In order to provide a unified analysis of the effects of worker characteristics on wage differentials, I compute residual wages from simple Mincer regressions by year. Separately for every year, I regress the log hourly wage (lsbrh) on a dummy for living in the Paris area (IDF), part-time status, gender, a polynomial of order four in labor market experience and occupation-industry dummies as in equation (2). For the subsample of workers in EAE-Trade-Panel, I use equation (3) and add a polynomial of order four in the tenure at the current firm.[24]

$$
\begin{aligned}
\mathsf{lsbrh}_i &= \beta_1 \mathsf{IDF}_i + \beta_2 \mathsf{partt}_i + \beta_3 \mathsf{sx}_i + \sum_{a=1}^{4} \alpha_a \mathsf{LMexp}_i^a + \gamma_{c,s} + \epsilon_i && (2) \\
\mathsf{lsbrh}_i &= \beta_1 \mathsf{IDF}_i + \beta_2 \mathsf{partt}_i + \beta_3 \mathsf{sx}_i + \sum_{a=1}^{4} \alpha_a \mathsf{LMexp}_i^a + \sum_{a'=1}^{4} \delta_{a'} \mathsf{tenure}_i^{a'} + \gamma_{c,s} + \epsilon_i && (3)
\end{aligned}
$$

The average residual wages by job status reported in table 3 reveal that observable characteristics explain some of the difference between the wage of new hires and other workers. The relative difference decreases from 17% to 9% in DADS-Postes once the controls of equation (2) are accounted for. It decreases further from 10% to 4% in DADS-Panel when I additionally control for the effect of tenure. Nevertheless, the difference remains significant whereas the residual wage accounting for tenure of separated workers is not statistically different from the residual of other workers.

To summarize, both separated and new workers have characteristics resulting overall in lower wages. There is no difference between the wage of separated workers and continued workers once these observable characteristics are controlled for. By contrast, there remains a significant difference between the residual wage of new hires and incumbent workers.

[23] Following a common practice in the labor literature, I define labor market experience as $\mathsf{age} - 18$.

[24] See subsections A.1 and A.2 in appendix for additional details about the construction of the residuals.

Table 3: Average characteristics of job flows: an overview.

Panel A.	Inflows ($t-1$,t)		
	All jobs	Continued jobs	New jobs
DADS-Postes:			
Number of jobs (millions)	23,35	19,90	3,45
	100%	85%	15%
Share of part-time jobs	4,92%	4,92%	6,67%
	(0,09)	(0,09)	(0,11)
Average experience	21,95	22,52	15,77
	(3,49)	(3,42)	(5,44)
Share of hours by female workers	27,7%	27,5%	29,9%
	(0,21)	(0,21)	(0,24)
Average log hourly wage	2,51	2,53	2,36
	(0,26)	(0,26)	(0,31)
Average log residual wage (1)	0,01	0,02	-0,06
	(0,14)	(0,14)	(0,16)
DADS-Panel:			
Number of jobs (thousands)	646,55	578,91	67,64
	100%	90%	11%
Average log residual wage (1)	0,03	0,03	-0,07
	(0,28)	(0,28)	(0,36)
Average log residual wage (2)	0,02	0,02	-0,02
	(0,28)	(0,28)	(0,36)

Panel B.	Outflows (t,$t+1$)		
	All jobs	Continued jobs	Terminated jobs
DADS-Postes:			
Number of jobs (millions)	21,55	18,28	3,27
	100%	85%	15%
Average experience	21,74	21,98	19,74
	(3,52)	(3,54)	(6,15)
Share of hours by female workers	27,4%	27,3%	29,6%
	(0,22)	(0,22)	(0,23)
Average log hourly wage	2,48	2,51	2,50
	(0,25)	(0,26)	(0,33)
Average log residual wage (1)	0,01	0,01	0,03
	(0,14)	(0,14)	(0,19)
DADS-Panel:			
Number of jobs (thousands)	646,55	570,01	76,54
	100%	88%	12%
Average log residual wage (1)	0,03	0,03	0,01
	(0,28)	(0,27)	(0,44)
Average log residual wage (2)	0,02	0,02	0,02
	(0,28)	(0,27)	(0,44)

Sources: DADS-Postes and DADS-Panel 1995-2007. In panel A, continued jobs refers to jobs that exist in both year $t-1$ and t while new jobs correspond to jobs that exist in year t but not in year $t-1$. In panel B, continued jobs refers to jobs that exist in both years t and $t+1$ while terminated jobs correspond to jobs that exist in year t but not in year $t+1$. In both panels, the number of jobs and average wages correspond to year t only. Averages and the associated standard deviations in brackets are computed using hours worked in t as weights. The log residual wages (1) and (2) come respectively from equations (2) and (3). Before pooling all years together, I adjust nominal variables to correct for inflation using a price index which is normalized to one in 2000.

4.2 The effect of firm growth on the characteristics of new and separated workers

Next, I consider variations in the characteristics and the wage of new and separated workers with firm growth. I substitute the separation rate in equation (1) with the wage and different average characteristics for new and separated workers. I implement the same specification as in column (13.C) of table 2 to estimate the effects of positive and negative growth. The coefficient estimates for the effect on wages are reported in the first column of tables 18 and 19 in appendix. The estimates for the other average characteristics are reported in table 15, 16 and 17.

Importantly, because I control for firm average workforce characteristics, the coefficients that are estimated are related to the characteristics of the transitioning workers *relative* to the rest of the workers in the firm.

I find that the wage of new hires increases with positive firm growth. This is consistent with the fact that larger positive firm growth is associated with the recruitment of more experienced workers that are less frequently hired part-time. The new recruits are also more likely to be poached from other firms and the job spells of the new hires are longer.

On the contrary, the wage of separated workers is unrelated to positive firm growth. This is the case despite the fact that separations at growing firms affect the relatively more experienced workers with slightly longer tenures at their firm (they were in the firm for a longer period). This latter result is hard to square with the findings of the previous section where it was shown that the increase in separations with firm growth resulted from the separations of recent hires. It would have been more consistent if the job spells of separated workers were decreasing with positive growth. This could mean that workers with long tenure are separated more often along with some recent hires.

I find that the wage of separated and hired workers at declining firms increases with the firm declining rate. With larger decline rates, the separated workers are relatively less experienced while the new hires are more experienced than the rest of the firm workforce.

This might come from the fact that firms laying-off workers *for economic* reasons have to separate with the workers who are more likely to find a new job because these workers tend to be the younger ones. Also, the larger the decline rate, the more often separations end up into transitions to a new job.

There are also clear trends for occupations but they seem unrelated to our findings on wages. The share of blue collar workers among hires increases with growth (for positive and negative rates) and the share of blue collars in separated workers increases with shrinking rates. The opposite is true for senior staff and supervisors. The separation of clerks is unrelated to growth rates but the share of clerks in hires increases with firm growth.

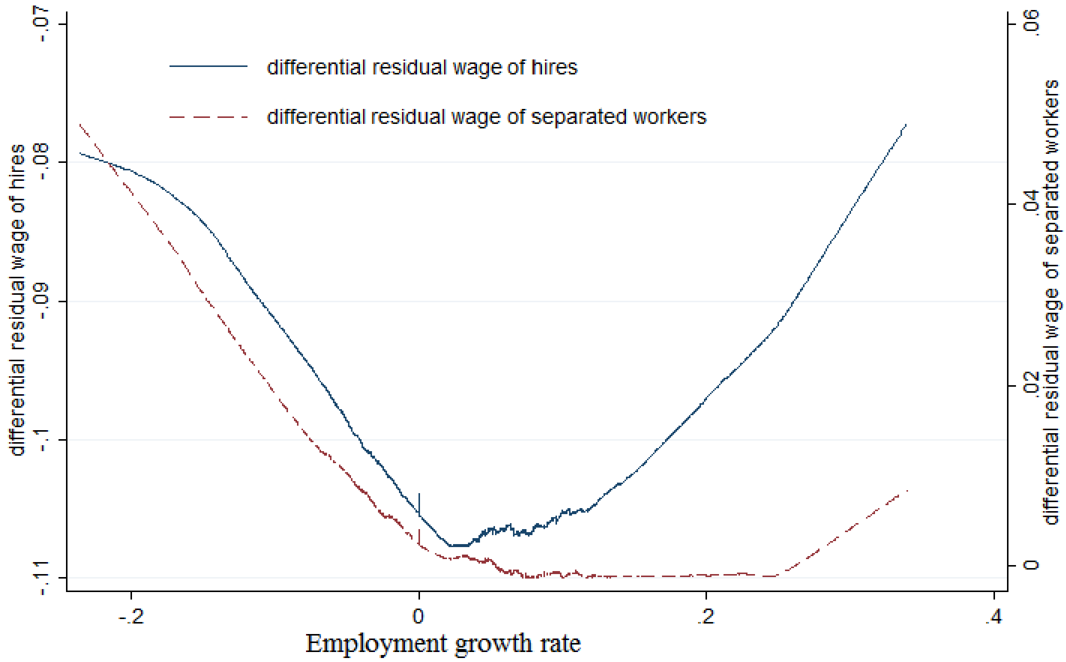
4.3 The effect of firm growth on the residual wage of new and separated workers

In the previous subsection, I show that the characteristics of new and separated workers vary with firm growth. In this subsection, I investigate whether these variations can explain the variation in the wage of new and separated workers. To this end, I relate the average of the residual wages computed from equation (2) to firm growth rates.

Figure 2 provides a first insight into the variation of residual wages. In this figure, the differential wages of new and separated workers are plotted against firm growth rates. I define the differential wages of hires as the difference between the average residual wage of new workers and the average residual wage of the rest of the the firm workforce. I also compute the same type of difference between the residual wage of separated and continued workers. Figure 2 reveals that faster growth is associated with higher wage offers but no variations for the wage of separated workers. It also shows that decline rates are associated with the separation of workers with higher residual wages and the recruitment of workers with higher residual wage.

The regression results in table 4 confirm the relevance and significance of the patterns in figure 2. At growing firms, both the wage and the residual wage of new hires increase

Figure 2: Change in the residual wage of new and separated workers with firm growth



Sources: EAE-Trade-Postes, 2000. The lines correspond to separate non-parametric bi-variate regressions of the wage differentials on job growth rates. The residual wage differentials are respectively the difference between the average wages of new and non-new workers, and the average wages of separated and non-separated workers. The construction of residual wages are described in section 4.1. 1% of the job growth rates were trimmed at both ends of the distribution.

significantly with the firm growth rate. When employment increases by 10%, the residual wage increases by 0.7%. This effect is highly significant and robust to the introduction of control for firm fixed and variable effects, to the use of alternative measures of growth, and to the restriction to single-establishment firms.[25] By contrast, the wage of separated workers is systematically unrelated to positive firm growth.

I test more thoroughly whether the relation between the wage offer differential and the firm hiring rate does not come from a composition effect by controlling for worker fixed characteristics. I follow the standard method developed in Abowd et al. (1999) [2] and use the matched worker-firm EAE-Trade-Panel dataset to control jointly for firm (FE), worker (WE), cohort (CE)and year effects (YE).

$$\mathsf{lsbrh}_{it} = \beta \mathsf{lhr}_{i,j(i,t)} + \phi Z_{i,t} + \mathsf{WE}_i + \mathsf{FE}_{j(i,t)} + \mathsf{CE}_{i,j(i,t)} + \mathsf{YE}_t + v_{i,t} \tag{4}$$

[25]See table 18 and 19 in appendix for robustness checks

Table 4: Residual wage elasticity of new and separated workers to firm growth.

	(18.A)	(18.B)	(18.C)	(19.A)	(19.B)	(19.C)
	New workers			Separated workers		
	log hourly wage	residual log wage	residual log wage	log hourly wage	residual log wage	residual log wage
max(0,growth rate)	0.124***	0.067***		-0.007	0.003	
	(0.014)	(0.012)		(0.014)	(0.010)	
min(growth rate,0)	-0.133***	-0.050***		-0.215***	-0.118***	
	(0.016)	(0.011)		(0.024)	(0.017)	
log hiring rate			0.019***			
			(0.002)			
log separation rate						0.013***
						(0.002)
Firm, year effects	YES	YES	YES	YES	YES	YES
Weights	Nin	Nin	Nin	Nou	Nou	Nou
Observations	181,704	181,704	181,704	179,852	179,852	179,852
R-squared	0.812	0.637	0.639	0.791	0.608	0.607

Sources: EAE-Trade-Postes 1995-2007. Specifications follow equation (1) with the average wages of transitioning workers as the dependent variable. The log hourly wage is used in columns A, while the residual log hourly wage obtained from equation (2) is used in columns B and C. All regressions include average workforce characteristics including the average residual wage in the rest of the workforce and other firm controls as detailed in the complete tables (18) and (19) in appendix. The regressions are weighted by the number of new (Nin) or separated workers (Nou). Firm-level clustered standard errors are in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

The firm that employs worker i at time t is indexed by $j(i,t)$. The cohort effect $\mathsf{CE}_{i,j(i,t)}$ are dummy variables corresponding to the year of hiring. The log hiring rate *at the time of hiring* $\mathsf{lhr}_{i,j(i,t)}$ is fixed over the job spell by definition.

The coefficient estimates of the log hiring rate lhr are reported in table 20 in appendix. The results indicates that the introduction of worker fixed effects have no significant impact on the coefficient estimates of the effect of firm growth. This implies that the worker characteristics we use when computing residual wages are good enough to control for worker composition effects. The inclusion of an indicator of job-to-job transition in the third specification shows that the effect of the hiring rate is not only due to higher bargaining power from already employed workers.[26] Moreover with the new specifications, the estimated effect of the hiring rate applies to the entire job-spell of new hires, demonstrating that the wage offer premium

[26]This prediction is at the heart of the wage bargaining model with on-the-job search of Cahuc et al. (2002).[16] Note that the indicator has a positive sign that is consistent with their theory.

is persistent.

For declining firms, the results in table 4 show that the wages and residual wages for both new and separated workers increase with the rate of decline. For separated workers, this could result from the French regulation on economic lay-offs specifying that workers with longer tenure must the last to leave. As more workers are laid-off, the average tenure and overall experience of separated worker increases. Since tenure is associated with higher wages, this drives the observed increase in the residual wage[27] of separated workers with decline rates. As regards new hires, the increase in the residual wage may be a risk premium offered to compensate workers from the risk that the firm may decline further and potentially exit in the future. This is supported by the the fact that job spells of new hires at declining firms decreases sharply with the decline rate.

5 The causal effect of growth on residual wages of hires

In this section, I examine the causal effect of increasing the hiring rate on the residual wage of new hires with an instrumental variable approach. Specifically I estimate the slope of the labor supply curve at the firm level.

Several firm-level shocks that are omitted in the analysis so far dampen the positive relationship between firm employment growth and wage offers. In particular, positive local labor supply shocks help the local firms to hire workers at lower wages. Also, firm level shocks to the recruiting technology allow firms to recruit more workers at lower wages. These shocks generate a downward bias of the coefficient estimate of the effect of the hiring rate.

I address the endogeneity concerns about the previous analysis by instrumenting firm hiring rates with the firm demand shock developed in Hummels et al. (2014).[25] In order to obtain a shock that is exogenous to labor market conditions in France, I use variations in foreign countries: the instrument is based on changes in the good demand from foreign countries. For this reason the instrument only applies to exporting firms.

[27]Here I use the residual wage obtained from equation 2 which does not include tenure.

In practice[28] I use the weighted average of the imports of foreign countries from the rest of the world but France. The weights are specific to firms indexed by j and depend on their export structure: I use the export share of product-destination in the first observed year of export[29], which I call the reference year $t_0(j)$. I call the firm-specific foreign demand FD_{jt}. Because firms are exposed to international trade to different extent, I scale foreign demand indexes by the share of exports in revenues in the reference year. Finally, I use the three-year moving average of the log foreign demand index in order to capture persistent demand shocks and eliminate outliers, and then take differences:

$$\mathsf{FDgr}_{j,t} = \Delta.\left(\frac{X_{j,t_0(j)}}{\mathsf{rev}_{j,t_0(j)}}\sum_{t'=-1..1}\left(\frac{\log \mathsf{FD}_{j,t}}{3}\right)\right) \tag{5}$$

In the first stage of the empirical model, measures of exporter growth (the log hiring rate lhr or positive and negative job growth, max(0jgr) and min(jgr,0)) are regressed on changes in foreign demand. In the second stage, the average residual log hourly wage ($\overline{\mathsf{lsbrh}}_{res}$) is regressed on predicted values of firm growth:

First stages:

$$\mathsf{lhr}_{j,t} = \delta_{max,0}\max(0,\mathsf{FDgr}_{j,t}) + \delta_{min,0}\min(\mathsf{FDgr}_{j,t},0) + \alpha_6.X_{j,t} + \nu_{0,j,t} \tag{6}$$

$$\max(0,\mathsf{jgr}_{j,t}) = \delta_{max,1}\max(0,\mathsf{FDgr}_{j,t}) + \delta_{min,1}\min(\mathsf{FDgr}_{j,t},0) + \alpha_7.X_{j,t} + \nu_{1,j,t} \tag{7}$$

$$\min(\mathsf{jgr}_{j,t},0) = \delta_{max,2}\max(0,\mathsf{FDgr}_{j,t}) + \delta_{min,2}\min(\mathsf{FDgr}_{j,t},0) + \alpha_8.X_{j,t} + \nu_{2,j,t} \tag{8}$$

Second stages:

$$\overline{\mathsf{lsbrh}}_{res,j,t} = \gamma\widehat{\mathsf{lhr}}_{j,t} + \alpha_9.X_{j,t} + \epsilon_{0,j,t} \tag{9}$$

$$\overline{\mathsf{lsbrh}}_{res,j,t} = \gamma_{max}\widehat{\max(0,\mathsf{jgr})}_{j,t} + \gamma_{min}\widehat{\min(\mathsf{jgr},0)}_{j,t} + \alpha_{10}.X_{j,t} + \epsilon_{j,t} \tag{10}$$

First stage results are presented in the bottom panel of table 5. Growth in foreign demand correctly predicts growth in the firm employment. The strength of the identification passes a first test as shown by the p-values of the F-test of exclusion of the instruments. The null

[28] See appendix section A.6 for technical details about data sources and the construction of the instrument.
[29] This first year correspond to the first year of the sample for the firms that started exporting before then.

Table 5: The causal effect of firm growth on the wage of new hires.

Second stage	(5.A)	(5.B)	(5.C)	(5.D)	(5.E) Single establishments	(5.F)
	OLS	2SLS	OLS	2SLS	OLS	2SLS
max(0,jgr)	0.081***	0.675*				
	(0.017)	(0.384)				
min(jgr,0)	-0.054***	-1.098				
	(0.013)	(1.015)				
log hiring rate			0.021***	0.104**	0.012***	0.100
			(0.002)	(0.047)	(0.002)	(0.114)
Under-identification p-value		0,107		0,001		0,098
Maximum remaining bias		<15%		<10%		>25%
Instrument validity J-test				0,222		0,261
Observations	105,133	105,133	105,133	105,133	76,578	76,578

First stage	max(0,jgr)	min(jgr,0)		log hiring rate		log hiring rate
max(0,FDgr)	0.210***	-0.025		1.426***		0.510*
	(0.077)	(0.036)		(0.415)		(0.272)
min(FDgr,0)	0.002	0.152*		0.193		0.271
	(0.147)	(0.086)		(0.798)		(0.712)
F-test of IV exclusion	0,0145	0,1982		0,0008		0,0957

Sources: EAE-Trade-Postes 1995-2007. Specifications follow equations (6)-(10). Average workforce characteristics and other firm controls are included as detailed in tables 21 and 22 in appendix. In column B, the job growth rates are instrumented as reported in the first two columns of the bottom panel. In columns D and F, the log hiring rate is instrumented as reported in the bottom panel. The regressions include firm and year effects and are weighted by the number of new workers (Nin). Firm-level clustered standard errors are in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

hypothesis is rejected at the 10% level for all measures of positive growth. I also address concerns about the validity of the exclusion restriction by controlling for a large set of firm variables including shares of hours by occupation category, shares of part-time and female workers, average experience in the workforce, average wage of incumbent workers, revenues, capital intensity, input purchases, investment rates, import decisions, imports and import growth.[30]

Second stage results are presented in the upper panel of table 5. P-values from the under-identification test demonstrate that the model is correctly identified. Instrumenting corrects for the expected downward bias as it systematically increases the coefficient estimate. In the first two 2SLS regressions, the maximum remaining bias of the IV estimates relative to the OLS estimates is estimated to be lower than 15%. Breaking down growth into its positive and negative components as in columns (5.A)-(5.B) yields imprecise estimates.Using the log hiring rate instead allows for more accurate results in the case of the full sample. The coefficient estimates are virtually unchanged where restricting the sample to single-establishment firms despite the fact that the significance test and the weak identification test are not passed anymore.

The new IV estimated value of γ is about .10, which is five times greater than the OLS estimate. The estimation result imply that an increase in the hiring rate by 10% requires a firm to raise wage offers by 1%. These values are larger but close to the estimates in Schmieder (2013) [38] who uses a slightly different measure of firm growth. In addition to the use of different independent variables, the difference in results could come from the different focus of his analysis. The study is about growth at small new establishments.[31] Because I focus on large, exporting firms, the difference between the two results could come from the effect of absolute growth in addition to the effect of relative growth.

[30] I also tried to control for the changes in these variables and the results remains the same

[31] Establishment age is the instrument variable used in his 2SLS approach and instrumenting increases its OLS coefficient estimate by 300% from .016 to 0.046

6 Conclusion

Despite a large literature on the role of firm growth in shaping worker flows, very little attention has been paid to the intriguing increase in separation rates with firm growth, and to the wages and characteristics of new and separated workers. This project contributes to the literature by studying empirically the characteristics of new hires, incumbent and separated workers across firms, within firms, and in response to foreign demand shocks.

I show that separations are an essential component of firm growth. The separation rate at growing firms increases when firms grow faster. This is a very robust pattern as it holds for a wide range of growth measures. Evidence on the characteristics of separated workers at growing firms are mixed. The increase in the number of separations at growing firms seems to mostly affect recent hires, but hires that stay have longer job spells at the firm than workers hired under other circumstances. Together, these facts support the view that firms actively search for good matches and more so when expanding.

I find that on average, separated workers are paid the same as continued workers. Distinguishing by firm growth rates, I find that the tenure of separated workers increases with the separation rate and that this is reflected in higher wages. This is likely to be the result of French regulation.

New hires are paid less than other workers but the bulk of the difference comes from differences in worker characteristics including tenure at the current employing firm. Wage offers to new hires increase with firm hiring rates as firms poach more often from other firms and hire more experienced workers. I also demonstrate the existence of a hiring differential, unrelated to worker characteristics, that increases with firm growth.

I interpret the positive association between the residual wages of hires and firm growth as evidence of an upward-sloping labor supply curve. I estimate the slope of the latter with an instrumental variable approach. I find that an increase in the log hiring rate of 10% causes a firm to increase wage offers by 1%. This estimate is coherent and complements earlier studies of the literature.

Overall, the findings strongly support the existence of firm-level labor frictions that are predicted by many models and which have important macro-economic consequences. In particular, these frictions could play an important role for wage inequality during transition periods with large reallocations across firms.

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Appendix

A Data appendix

In summary, the study focuses on the period 1995-2007 and on the firms present in the census of manufacturing firms of 20+ workers (EAE). I exclude from the analysis a number of very large firms and firms in the aerospace industries that undergo a large number of mergers & acquisitions and changes in their organization and legal status.[32] I obtain worker and job level information from the mandatory reports on worker earnings of two DADS datasets (DADS-Postes and DADS-Panel). I supplement these information with trade level data from the French customs and from the United Nations.

In every datasets, I drop the observations that have an invalid or temporary firm identifier following the procedure described on the French wikipedia page about the SIREN identifying code. I also drop public firms.[33]

A.1 Exhaustive job-level data and job flows: DADS Postes

A.1.1 Original job-level data

The dataset is constructed and maintained by the National Institute of Statistics and Economic Studies (henceforth the INSEE) based on the mandatory reports that every firm must file for each of its establishments to the *Sécurité Sociale* government agencies.[34] The data cover all private and semi-public establishments but exclude household services (NAF 95: *services domestiques*), foreign activities (NAF 99: *activités extra-territoriales*) and up to 2002, the data also exclude agricultural employees (*salariés de l'agriculture*).

The dataset starts in 1995. In order to avoid complications related to changes in classi-

[32]See subsection A.3 for more details.

[33]These firms have a SIREN identifier starting with one or two.

[34]If every firm must report to the *Sécurité Sociale*, only the establishments in the private and semi-public sectors are included in the original dataset.

fications[35] and specific macro trends, I drop the years corresponding to the great recession and restrict the analysis to the years 1995-2007.

The unit of observation is a job, defined as a pair of worker-firm in a given year.[36] Firms are identified by their administrative SIREN codes which can be used to match data from different datasets at the firm level. By contrast, worker data is anonymized. The data consist of a pool of overlapping two-year panels of jobs: for each year, the past characteristics of every jobs that existed in the previous year are reported. However, the absence of a consistent worker or job identifiers across years makes it impossible to organize the data in a full panel.[37] For each job, I use the following information provided by the dataset:

- Gender and age
- Occupation classification (*Catégories Socioprofessionnelles*) with five categories[38]
- Region of residence
- Job type (full, part time, and others.)
- Total hours worked
- Nominal before and after tax earnings in current euros
- Industry classification of the establishment (*Activité Principale Excercée*) according to the *Nomenclature d'activités française* (henceforth NAF[39])
- Job status in the current year ("principal"[40], "side"[41], or terminated last year)

[35] In particular, the industry classification changes in 2008.

[36] The data is originally at the worker-establishment level but because the establishment identifier cannot be used to match the data with any other dataset and because it is quite inconsistent across years, I collapse the data at the firm level

[37] In particular, worker identifiers are only introduced in 2002 and are only consistent whithin each two-year panel.

[38] I follow Caliendo et al. (2015) [?] and use the code numbers two to six associated to the five following corresponding categories: 2. firm owners receiving a wage which includes the CEO or firm directors; 3. senior staff or top management positions which includes chief financial officers, heads of human resources, and logistics and purchasing managers; 4. employees at the supervisor level which includes quality control technicians, technical, accounting, and sales supervisors; 5. qualified and non qualified clerical employees, secretaries, human resources or accounting employees, telephone operators, and sales employees; 6. blue-collar qualified and non qualified workers welders, assemblers, machine operators, and maintenance workers. These codes correspond to the first digit of the original classification.

[39] I group a few of the 672 industries in order to obtain a classification that is consistent over the years of the sample period. Whenever missing, the industry classification of a firm is imputed using the industry code of the establishment with the largest number of workers or using the firm past or future industry codes.

[40] An individual can have more than one "principal" job in a given year.

[41] A job is either a "principal" or a "side" job. Side jobs are jobs with a number of hours and earnings below certain thresholds. There is a break in the treatment of variables in 2002 which specifically affects the break down of jobs into "principal" or "side" job. I choose to use the full 1995-2007 period anyway in order to have time series that are long enough to allow for identification strategies that rely on job-switching. In

- Job status in the previous year ("principal", "side", or not started yet)

along with the previous year occupation code, earnings, hours worked if the job existed then.

A.1.2 Construction of new variables

I define the following variables for the current and/or past years whenever possible:

- IDF: a dummy for residence in the Paris area:
- partt: a dummy for part time jobs[42]
- LMexp=age−18: labor market experience
- lsbrh: the log hourly wage defined as the log ratio of before-tax earnings to hours
- lsbrh_res: the residual log hourly wage which is obtained from equation (2) below. It includes a polynomial in experience, and occupation-industry fixed effects indexed by c and s. Industries are here defined by the first two digits of the NAF. The regression is implemented separately in every year.

$$\mathsf{lsbrh}_i = \beta_1 \mathsf{IDF}_i + \beta_2 \mathsf{partt}_i + \beta_3 \mathsf{sx}_i + \sum_{a=1..4} \alpha_a \mathsf{LMexp}_i^a + \gamma_{c,s} + \epsilon_i \tag{2}$$

- arriv: an indicator of new jobs for principal jobs that takes one if the same job did not exist or was not a main job in the previous year

I duplicate and format the data to construct another pool of overlapping two-year panels with information about the current and future characteristics of jobs. This allows me to construct an indicator of ending "principal" jobs that takes one if the same job does not exist or is not a "principal" job in the next year: leave.

I drop jobs with either zero hours or no earnings (in the current or past year of every two-year panel). I trim the log hourly wage residual and drop the observations with values that are more than five standard deviations away from annual averages.

2002-2007 in the general case, a job is characterized as "principal" if the corresponding annual net earnings are above three monthly minimum wages or if the number of days worked is more than 30, the number of hours worked is above 120 and the the ratio of hours to days is above 1.5. In 1995-2001, the earnings thresholds are defined in francs for each year (around 16000frcs) and the time threshold is simply 300 hours.

[42] In 1994-2001, a job is full time if CIPDZ is "*C: complet*" and part-time otherwise ("*I: Intermittent*", "*P: temps partiel*","*D: Travail à domicile*" or "*R: Rappel de l'année précédente*"). In 2002-2008, a job is full time if CPFD is "*C: complet*" or "*K: Postes à condition d'emploi mixte à dominante temps complet*" and part-time otherwise ("*P: temps partiel*", "*F: faible temps partiel*", "*D: Travail à domicile*" or "*Y: Postes à condition d'emploi mixte à dominante temps partiel*").

I report in table 6 the average characteristics of job flows for the universe of private sector jobs in years 1995-2007 before the selection of any observations or industries. I have defined "continued" jobs as the jobs that are observed in the two successive years of two-year panels. The turnover of jobs is very high: 35% of the jobs in a given year are not continued in the following year and 36% of the jobs did not exist the year before. This may results from undue changes in firm identifiers or the existence of a large number of short-lived jobs. I try to assess the relevance of these two hypotheses in the following sections.

The average hourly wages reported in table 6 shows that continued jobs pay better than the new and terminated jobs. Given the number of observations, the differences are significant (the p-values are well below 1%). A substantive fraction of the differences between wages can be explained by the composition of jobs: the difference in average log residual wages is smaller once differences in labor market experience, gender and occupation shares are accounted for as in equation (2). However, while the difference between the residual wage of terminated and continued workers becomes insignificant, the difference between the residual wage of new and continued workers does not vanish. I show later that some of the latter difference is explained by differences in tenures at the current firm.

A.1.3 Aggregation and the construction of a firm level dataset

In the next step, I aggregate data at the firm level by summing values or by computing weighted averages using hours worked as weights. For every firm, I construct the following variables:

- Nempl: number of jobs in a given year (i.e. the number of different workers)
- Nnic: number of establishments in a given year
- nbheur: number of hours worked in the firm
- N_ageXX: fraction of hours worked[43] for each of five age bins ($XX \in \{1..5\}$)
- NcsXX: fraction of hours worked for each of the five occupations ($XX \in \{2..6\}$)
- N_F: fraction of hours worked by female workers
- N_partt: fraction of hours worked in part-time jobs

[43]The cutoffs used to define the bins are at age 25, 32, 40, and 48.

Table 6: Job flow characteristics in DADS-Postes.

Panel A.	Inflows ($t-1$,t)		
	All jobs	Continued jobs	New jobs
Number of firms (millions)	3,29	3,29	2,95
Number of observations (millions)	20,70	20,70	12,28
Number of jobs (millions)	304,70	195,60	109,10
	100%	64%	36%
Hours worked (billions)	399,20	307,00	91,49
	100%	77%	23%
Hourly wage	12,8	13,2	11,58
	(4,91)	(5,21)	(5,13)
Share of part-time jobs	13,83%	13,83%	19,53%
	(0,19)	(0,16)	(0,27)
Average experience	20,64	21,77	16,94
	(5,56)	(4,64)	(7,86)
Share of hours by female workers	41,5%	41,9%	40,2%
	(0,28)	(0,27)	(0,29)
Average log hourly wage	2,41	2,45	2,31
	(0,32)	(0,31)	(0,36)
Average log residual wage (1)	0,00	0,01	-0,04
	(0,17)	(0,17)	(0,20)

Panel B.	Outflows (t,$t+1$)		
	All jobs	Continued jobs	Terminated jobs
Number of firms (millions)	3,31	3,31	3,01
Number of observations (millions)	20,90	20,90	12,16
Number of jobs (millions)	304,50	199,10	105,40
	100%	65%	35%
Hours worked (billions)	399,00	308,30	90,05
	100%	77%	23%
Hourly wage	12,83	13,01	12,28
	(4,96)	(5,00)	(5,57)
Average experience	20,63	21,45	17,85
	(5,55)	2(5,19)	(8,21)
Share of hours by female workers	41,5%	41,9%	39,8%
	(0,28)	(0,65)	(0,29)
Average log hourly wage	2,41	2,44	2,36
	(0,32)	(0,31)	(0,37)
Average log residual wage (1)	0,00	0,00	0,00
	(0,17)	(0,17)	(0,20)

Sources: DADS-Postes 1995-2007. In panel A, continued jobs refers to jobs that exist in both year $t-1$ and t while new jobs correspond to jobs that exist in year t but not in year $t-1$. In panel B, continued jobs refers to jobs that exist in both years t and $t+1$ while terminated jobs correspond to jobs that exist in year t but not in year $t+1$. In both panels, the number of jobs, hours worked and average wages correspond to year t only. Averages and the associated standard deviations in brackets are computed using hours worked in t as weights. The weights used to compute the average change in the log hourly wage are the sum of the hours worked in the two years of the two-year panels. The log residual wage comes from equation (2) and is defined in the main text. Before pooling all years together, I adjust nominal variables to correct for inflation using a price index which is normalized to one in 2000.

- N_LMexp: weighted average labor market experience of workers
- s_br: labor compensation paid by the firm
- lsbrh: weighted average log hourly wage using hours worked as weights
- lsbrh_res: weighted average of the residual log hourly wages
- arriv: share of new hires in total workforce (headcount)
- leave: share of future separated workers in total workforce (headcount)

For every firm, I also compute the weighted average characteristics of jobs (log hourly wages, log residual wage, labor market experience, gender, part-time, occupation shares) by job-flow status (continued, new, and terminated). The variables corresponding to averages for new hires start with in_, the ones for non-new hires with nin_, the ones for future separated workers with out_ and the ones with non separated workers with nou_.

A.1.4 Definitions of worker flow measures

To characterize worker flows at the firm level, I construct the following measures. I define the number of jobs in the year (Njob) as the total number of different workers employed in a year (Nempl) minus the number of replacements, which corresponds to the minimum between the number of new hires ($\mathsf{arriv}_t * \mathsf{Nempl}_t$) and the number of separations ($\mathsf{leave\_1}_{t+1} * \mathsf{Nempl\_1}_{t+1}$):

$$\mathsf{Njob}_t = \mathsf{Nempl}_t - \min(\mathsf{arriv}_t * \mathsf{Nempl}_t, \mathsf{leave\_1}_{t+1} * \mathsf{Nempl\_1}_{t+1}) \tag{11}$$

I define the initial number of jobs as the difference between the number of jobs and the net change in the number of workers ($\mathsf{Njob}_t - \mathsf{arriv}_t * \mathsf{Nempl}_t + \mathsf{leave\_1}_{t+1} * \mathsf{Nempl\_1}_{t+1}$). Then I define the average number of jobs in a year (Njobavg) as the average between the initial number of jobs and the number of jobs.

$$\begin{aligned}\mathsf{Njobavg}_t &= \frac{1}{2}[(\mathsf{Njob}_t - \mathsf{arriv}_t * \mathsf{Nempl}_t + \mathsf{leave\_1}_{t+1} * \mathsf{Nempl\_1}_{t+1}) + \mathsf{Njob}_t] \\ &= \mathsf{Njob}_t - \frac{1}{2}(\mathsf{arriv}_t * \mathsf{Nempl}_t - \mathsf{leave\_1}_{t+1} * \mathsf{Nempl\_1}_{t+1}) \end{aligned} \tag{12}$$

The growth in the number of jobs is constructed as the ratio of the net change in the number of jobs within the period to the average number of jobs:

$$\mathsf{jgr}_t = \frac{\mathsf{arriv}_t * \mathsf{Nempl}_t - \mathsf{leave\_1}_{t+1} * \mathsf{Nempl\_1}_{t+1}}{\mathsf{Njobavg}_t} \tag{13}$$

This definition ensures that the denominator is never null.

I define the hiring and the separation rates (hr and sr) as follows:

$$\mathsf{hr}_t = \frac{\mathsf{arriv}_t * \mathsf{Nempl}_t}{\mathsf{Njobavg}_t} \quad \text{and} \quad \mathsf{sr}_t = \frac{\mathsf{leave\_1}_{t+1} * \mathsf{Nempl\_1}_{t+1}}{\mathsf{Njobavg}_t} \tag{14}$$

and this implies that $\mathsf{hr}_t - \mathsf{sr}_t = \mathsf{jgr}_t$.

A.2 Job-level sample on career evolutions of workers: DADS Panel

A.2.1 Original and new constructed variables

This dataset is based on the same underlying data used in the construction of the DADS-Postes dataset. The dataset is also constructed and maintained by the INSEE. There are two important differences between the two datasets. First, DADS-Panel only includes the subsample of individuals born in October of even years.[44] Second, it is a true worker panel as the sampled individuals are followed across jobs and over the entire 1994-2008 period.

As in DADS-Postes, for every worker in any year, the data provides information about her age (age), gender (sx), and her region of residence (depR) from which I construct a dummy variable for being a resident of the Paris area (IDF). For every job in any year, i.e for every worker-firm-year triplet, the data provides an occupation code (cs1)[45], part-time status (partt), before tax earnings adjusted for inflation[46] (sbr), number of hours worked (nbheur),

[44]Starting from 2002, the individuals born in October of odd years are included. These individuals are identified by the variable pan25 which takes the value zero in this case. Nevertheless I chose to ignore these individual to keep a similar number of observations over the period.
[45]See footnote 38 for more details.
[46]The price index is re-coded to be equal to one in 2000.

the start and end dates within the current year (debremu and finremu), and the year of entry in the firm (entsir).

The definitions of new and terminated jobs differ slightly the definitions of DADS-Postes variables in order to make use of the specificity of the full panel structure of DADS-Panel. I define indicators for new hires (new), separations (sep) and job-to-job transitions (ljtjin and ljtjou):

- new: new hires, specifically jobs that are never observed in previous years[47]
- ljtjin: indicator of new hires that were observed at another firm in the last 15 days[48]
- sep: separations, specifically jobs that are never observed in subsequent years[49]
- ljtjou: indicator of separated workers that were at another firm in the next 15 days.
- lsbrh_res and lsbrh_res2: residual log hourly wages, respectively obtained from equation 2 and from the same equation augmented with a tenure polynomial:

$$\mathsf{lsbrh}_i = \beta_1 \mathsf{IDF}_i + \beta_2 \mathsf{partt}_i + \beta_3 \mathsf{sx}_i + \sum_{a=1..4} \alpha_a \mathsf{LMexp}_i^a + \sum_{a'=1..4} \delta_{a'} \mathsf{tenure}_i^{a'} + \gamma_{c,s} + \epsilon_i \tag{3}$$

A.2.2 Exclusion of outliers and insignificant jobs

First I chose to drop all the "side" jobs in order to focus on the jobs that are likely to better reflect the potential of workers. Then I drop 11% of the remaining observations that have missing or unusual values. Specifically, I drop the observations for which the residual wage of a Mincer regression is five standard deviations away from the sample mean (1.1% of observations). I drop the observations with a ratio of hours per week worked that is below 33% of 35 hours per week (+3.4%). I drop the observations with more than three different jobs in a given year (+0.5%). I drop the observations with age below 16 or above 65 (+0.3%). Finally, I drop the observations with incorrect worker identifiers (+5.7%).

An important difference between DADS-Postes and DADS-Panel is that I drop "side" jobs

[47]As in DADS-Postes, I only take "principal" jobs into account. I use the information in year 1994 in order to be able to construct the values in 1995.

[48]The choice of 15 days follows Postel-Vinay and Robin (2002) [?] . Implicitly, this means that transitions from and to the excluded sectors (namely in agriculture, in the public sector or in household services) are not counted as job-to-job transitions.

[49]I use the information in year 2008 in order to be able to construct the values in 2007.

in the latter. I use DADS-Postes to have information about the entire workforce of firms and account for the entire worker flows in and out firms. By contrast, I use DADS-Panel to have information about the career evolution of workers over time and across meaningful jobs.

A.3 Firm level data on manufacturing production: EAE data

The census of manufacturing (*Enqête Annuelle d' Entreprise*, henceforth EAE) is conducted by the INSEE and covers the private firms of 20 workers or more in manufacturing industries (NAF codes 10 to 39) over the period 1995-2007. It includes firms in the energy sector but excludes the agri-food industries. As in the DADS datasets, firms are identified by their administrative SIREN code.

The census contains standard annual balance-sheet information including average and end-of-period employment, total and export revenues, total worker compensation, material expenditure, value-added before tax and after depreciation transfers, profits computed as operating profits minus taxes and interests, beginning- and end-of-period physical capital stock.

The INSEE warns that a handful of large multi-firm groups tend to report all of their workforce in some of their firms and their revenues in others. The INSEE has tried to consolidate the data at the group level but data from the consolidated groups cannot be matched to firm-level data from other datasets anymore. In addition, a small number of large public companies in the energy and aerospace sectors were privatized and extensively re-organized during the period. Therefore these firms were included in the EAE census in the middle of the period and experienced many changes in SIREN codes. Because of these issues and because these large groups (denoted by an indicator, groups)[50] are likely to have significant market power in the French labor market, I exclude them from most of the analysis.

[50] In particular the car-makers Renault and Peugeot, the formerly public companies EDF, GDF, SUEZ in the energy sector as well as AIRBUS and SeB were excluded from the analysis.

A.4 Firm level data on French trade: customs data

The customs data are provided by the Direction générale des Douanes et Droits Indirects which is the national agency in charge of constructing the trade balance of goods in France. The dataset covers the period 1994-2010 but I restrict the analysis to the years before 2008.

The data is a census at the firm level of the goods traded with countries that are not members of the European customs union. Since 1993 and the beginning of the European customs union, data on trade with members of the union is collected differently from the rest of international trade data. Firms that engage in intra-union trade are only required to report the transactions whose value is above a certain threshold. This threshold was 250,000 frcs in 1993, is raised to 650,000 frcs in 2001, to 100,000€ in 2002, 150,000€ in 2006 and to 460,000€ in 2011.[51] Firms are identified by their administrative SIREN code as in the other datasets.

The dataset reports values and quantities of exports and imports by destination and origin and by product code of the 8-digit Combined Nomenclature (CN8). I aggregate product categories to use the more commonly used 6-digit Harmonized System (HS6). This is necessary when I match the data with the imports of foreign countries. Furthermore, I implement the algorithm for harmonizing the HS6 export and import codes over time following the method developed in Pierce and Schott (2012).[34]

I drop trade with the overseas departments and territories of France (DOM/TOM)[52] as they are gradually dropped from the international trade statistics over the period. In order to be consistent with the data on world trade that is also used in this work, I aggregate Belgium and Luxembourg, Switzerland and Lichtenstein, the country members of former Yugoslavia (Serbia, Montenegro, and Kosovo), as well as the members of the South African customs union (Bostwana, Lesotho, Namibia and Swaziland). After these aggregations, the

[51] Other breaks in data collection include changes in the FoB/CIF rate in 1998, 1999, 2000, 2001, 2004 and 2009.

[52] Guadeloupe, Guyane française, Martinique et Réunion are anyway excluded from the original data since 1997. Mayotte is excluded since 2014.

dataset consists of 168 countries and aggregate regions.

A.5 Country level data on world trade: BACI

I obtain world data on imports by origin and destination at the HS6 product level for the years 1995-2007 from the *Base pour l'Analyse du Commerce International* (henceforth BACI) developed by the CEPII [24] and based on the United Nations Statistics Division's COMTRADE database. I group countries and harmonize the HS6 export and import codes over time in the same way as I did for the French customs data.

A.6 Merging and formating EAE and trade data

A.6.1 Customs data and BACI: constructing firm foreign demand indexes

This subsection describes in details the construction of the instrument used in the main text, namely the firm-specific foreign demand index.

To this end, I start with the firm-level customs data on exports by product and destination. I define reference years $t_0(j)$ for every firm j as the first year in which I observe positive export values. For every triplet firm-product-destination indexed by (j, p, c) in the reference year $t_0(j)$, I associate the corresponding sum of imports across all origin countries except France in every year $t \geq t_0$ from BACI ($M_{p,c,t} = \sum_{c' \neq FR} M_{p,c \leftarrow c',t}$). This represents the demand in product p of destination c. Less than 1% of the firm observations have no match in the world trade dataset of BACI and this corresponds to less than 0.1% of the total export values in reference years.

In a second step, I compute two market shares and exclude the observations with high market share values. First, for every firm-product-destination, I compute the ratios of imports from the firm ($X_{j,d,c,t_0(j)}$) to all imports by destination-product ($M_{p,c,t_0(j)}$) in the reference year $t_0(j)$. These ratios $\left(\frac{X_{j,p,c,t_0(j)}}{M_{p,c,t_0(j)}}\right)$ represent the import share of firm exports by destination-product. Second I compute the ratio of firm exports ($X_{j,p,c,t_0(j)}$) to the sum of

French exports by destination-products ($X_{FR,p,c,t_0(j)}$). These ratios $\left(\frac{X_{j,p,c,t_0(j)}}{X_{FR,p,c,t_0(j)}}\right)$ represent the export share of firm exports by destination-product. I drop firm-product-destination observations when the import share exceeds 33%, when the export share exceeds 50%, and for exports to DOM/TOM and to unknown destinations. I denote the groups of excluded product-destination by firm with $\Xi(j)$. I exclude these destination-product pairs in order to avoid possible reverse causality issues in the IV analysis.

In the third and last step, I construct the firm-specific foreign demand index as the weighted sum of world imports ($M_{j,d,t}$) and normalize it to be one in the reference year. The weights are given by firm exports in the reference year.

$$\log \mathsf{FD}_{j,t} = \log\left(\sum_{(p,c)\notin\Xi(j)} \omega_{j,p,c}\frac{M_{p,c,t}}{M_{p,c,t_0(j)}}\right) \qquad \text{with} \quad \omega_{j,p,c} = \frac{X_{j,p,c,t_0(j)}}{\sum_{(p,c)\notin\Xi(j)} X_{j,p,c,t_0(j)}} \tag{15}$$

The difference in consecutive log indexes ($\Delta \log \mathsf{FD}_{j,t} = \log \mathsf{FD}_{j,t} - \log \mathsf{FD}_{j,t-1}$) represents the growth rate in average foreign demand for the goods that a firm produced in its reference year. Note that the variable FD is constructed for the year 1995-2007 because world trade data from BACI are only available since 1995.

A.6.2 Merging EAE and trade data

I merge the EAE dataset with the customs data at the firm-year level after having aggregated the customs data across products and destination/origin countries. 90% of the observations in EAE are matched with data from the French customs because there is a firm record of either exports or imports. Then I add the time varying firm level instrument variable constructed with the world trade data of BACI. Of the EAE-customs matched observations, 80% have non-missing values for the constructed firm foreign demand instrument. Observations with non-missing values for the instrument account for 98.5% of all the revenues generated by EAE firms in 1995-2007.

Finally, I focus on persistent demand shocks and eliminate outliers by taking the three-year moving average of the index. o avoid having a missing value in the first year, I take the average of the first two foreign demand indexes with weights two third and one third respectively. Ultimately in the analysis, I use the difference index scaled by using the ratio of exports to revenues (rev) in the reference year:

$$\mathsf{FDgr}_{j,t} = \left(\frac{\sum_{(p,c)\notin\Xi(j)} X_{j,p,c,t_0(j)}}{\mathsf{rev}_{j,t_0(j)}} \right) .\Delta \left(\sum_{t'=-1..1} \left(\frac{\log \mathsf{FD}_{j,t}}{3} \right) \right) \qquad (5')$$

A.7 The EAE-Trade-Postes dataset on firm level worker flows

A.7.1 Merging DADS-Postes and EAE-Trade datasets

I merge the DADS-Postes aggregated firm-level dataset with the EAE-trade constructed dataset based on SIREN codes and years. EAE-DADS matched observations account for 8% of the observations and 39% of the employment count in DADS-Postes. The quality of the matching of EAE firms is good because DADS-Postes covers the universe of private firms: 95% of the firm-year in the initial EAE dataset are matched with data from DADS-Postes. The matched observations account for 94% of total employment in EAE and 5.5% of the unmatched employment comes from the handful of big French corporate groups that have SIREN identifier issues.[53] The other unmatched observations consist of very small firms with an average of 81 employees instead of 121 for the matched observations.

A.7.2 Trimming outliers and observations with inconsistent values

I perform several verifications and drop the observations with abnormal values. Redundancy of variables in the overlapping two-year panels of DADS-Postes[54] and the presence of employment variables in both the DADS-Postes and EAE datasets allows for various checks. Specifically I exclude the firm-year observations:

[53]See the end of section A.3 for more details.

[54]Every firm that is active in two consecutive years t and $t+1$ appears in two of the overlapping panels. Therefore the wages it pays and the number of hours worked in year t are given twice by the variables in each panel: I would have $\mathsf{s\_br}_t = \mathsf{s\_br\_1}_{t+1}$ and $\mathsf{nbheur}_t = \mathsf{nbheur\_1}_{t+1}$ if there were no errors.

- when the firm is observed in only one of the two-year panel (it enters or exits DADS)
- when wage or employment values are inconsistent across overlapping two-year panels $\left(\mathsf{Ibad}_t = \mathbb{I}\left\{\left|1-\frac{\mathsf{s\_br\_1}_{t+1}}{\mathsf{s\_br}_t}\right| \geq 1 \text{ or } \left|1-\frac{\mathsf{Nempl\_1}_{t+1}}{\mathsf{Nempl}_t}\right| \geq 1\right\}\right)$
- when the firm belongs to the problematic big groups of firms
- when all jobs in a firm are classified as new jobs or terminated jobs ($\mathsf{Isuspi}_t = \mathbb{I}\left\{\mathsf{Ibad}_t = 1 \text{ or } \mathsf{groups} = 1 \text{ or } \mathsf{arriv}_t \geq 1 \text{ or } \mathsf{leave\_1}_t \geq 1\right\}$)
- when in a given year, the employment growth rate is in one the two extreme percentiles ($\mathsf{Isuspi}_t = \mathbb{I}\left\{\mathsf{Ibad}_t = 1 \text{ or } \mathsf{groups} = 1 \text{ or } \mathsf{jgr}_t \leq P1_t \text{ or } P99_t \leq \mathsf{jgr}_t\right\}$)
- when employment data is inconsistent across datasets (Njob is the job count in DADS and E200 is the EAE measure of employment) $\left(\mathsf{Iincons}_t = \mathbb{I}\left\{\mathsf{Isuspi}_t = 1 \text{ or } \mathsf{Isuspi}_{t+1} = 1 \text{ or } \left|\frac{\mathsf{Njob}_t}{\mathsf{E200}_t} - 1\right| \geq .5\right\}\right)$

32% of matched EAE-DADS observations are hence excluded and the bulk of the exclusion (30%) comes from missing values (of one of the four variables needed in Iincons) that prevents the implementation of checks. Non-excluded observations account for 82% of the total EAE employment in EAE-DADS matched observations.

In most of the analysis, I also exclude the observations when firms changed their number of establishments ($\Delta\mathsf{Nnic} \neq 0$). With this restriction I seek to rule out firm growth via mergers and acquisitions which is out of the scope of the present analysis. This leads me to drop an additional 7% of the matched EAE-Postes observations and a corresponding additional 23% of EAE-Postes employment. I call this dataset the selected EAE-Trade-Postes sample.

A.7.3 Descriptive statistics about the selected EAE-Trade-Postes sample

The main characteristics of the constructed EAE-Trade-Postes dataset are reported in tables 7 and 8. The hours and average wages by job category reported in table 7 can be compared to those of the full data reported in table 6. The restriction to manufacturing firms, the exclusion of outlying values and the exclusion of the years of entry and exit of firms in the data impact the values substantially. First of all, the shares of new and terminated values is considerably smaller in the EAE-Trade-Postes subsample. Second, there are less women working in manufacturing industries and less part-time workers. Last but not least, the average wages are higher in the selected subsample.

A.8 The EAE-Trade-Panel datasets on worker career evolutions

A.8.1 Merging EAE-Trade-Postes and DADS-Panel datasets

I supplement the DADS panel of individuals with the firm variables in EAE-Trade-Postes. The two datasets are merged based on SIREN codes and years. The matching rates for the individuals working in EAE manufacturing industries is good: 97% of these DADS-Panel observations have a match in DADS-Postes.[55]

A.8.2 Selection of a connected group of workers and trimming of outliers

I restrict the sample to workers of manufacturing industries and select a subsample of firms with a minimum of sampled workers. Specifically I only keep the individuals that worked at least once in a manufacturing firm. Then I follow Woodcock (2007) [40] and drop all firms that have four or less workers in the dataset. Finally I follow Abowd et al. (1999) [2] and select the largest connected group in the sample. This connected group is the largest group of firms that are linked to each other by workers who switched from one firm to another. These selections of observations are meant to restrict the sample to the observations that allow for the identification of firm and worker fixed effects. From then on, I call this new merged dataset EAE-Trade-Panel.

While the initial DADS-Panel data with workers in every sectors had about 11.5 million observations and 1.5 million workers, the new EAE-Trade-Panel dataset consists of 1,709,009 observations, 16,843 firms, 248,813 workers and 523,428 jobs. Of these, 1,337,472 observations, 11,457 firms, 225,776 workers and 306598 jobs are at firms in EAE.

[55]For the full DADS-Panel data, matches account for 51% of the observations. The low matching rates comes from the fact that EAE-Trade-Postes only includes manufacturing firms.

Table 7: Job flow characteristics in the selected EAE-Trade-Postes sample.

Panel A.	Inflows ($t-1$,t)		
	All jobs	Continued jobs	New jobs
Number of firms	33 897	33 897	33 577
Number of observations	209 264	209 264	202 536
Number of jobs (millions)	23,35	19,90	3,45
	100%	85%	15%
Hours worked (billions)	38,02	34,78	3,22
	100%	92%	8%
Hourly wage	13,94	14,09	12,45
	(4,02)	(4,06)	(4,82)
Share of part-time jobs	4,92%	4,92%	6,67%
	(0,09)	(0,09)	(0,11)
Average experience	21,95	22,52	15,77
	(3,49)	(3,42)	(5,44)
Share of hours by female workers	27,7%	27,5%	29,9%
	(0,21)	(0,21)	(0,24)
Average log hourly wage	2,51	2,53	2,36
	(0,26)	(0,26)	(0,31)
Average log residual wage (1)	0,01	0,02	-0,06
	(0,14)	(0,14)	(0,16)

Panel B.	Outflows (t,$t+1$)		
	All jobs	Continued jobs	Terminated jobs
Number of firms	32 489	32 489	32 287
Number of observations	193 303	193 303	189 189
Number of jobs (millions)	21,55	18,28	3,27
	100%	85%	15%
Hours worked (billions)	34,79	31,73	3,051
	100%	91%	9%
Hourly wage	13,84	13,76	14,72
	(3,96)	(3,90)	(5,79)
Average experience	21,74	21,98	19,74
	(3,52)	(3,54)	(6,15)
Share of hours by female workers	27,4%	27,3%	29,6%
	(0,22)	(0,22)	(0,23)
Average log hourly wage	2,48	2,51	2,50
	(0,25)	(0,26)	(0,33)
Average log residual wage (1)	0,01	0,01	0,03
	(0,14)	(0,14)	(0,19)

Sources: DADS-Postes 1995-2007. The variables, the averages and standard deviations are defined in the legend of table 6. Nevertheless, there are two differences with table 6. First, the values are computed using firm totals and averages instead of disaggregated job values. Second, the values are computed on the subsample of the data defined in subsection A.7.2.

Table 8: Firm average characteristics by growth status in EAE-Trade-Postes.

	All firms		Firm growth status: Declining		Stable		Growing	
number of firms	33 897							
number of observations	209 264		92 911		22 545		93 808	
EAE variables:								
sales (1000,000€)	18,4	(88,8)	20,2	(98,4)	7,2	(28,6)	19,4	(88,1)
employment	98,9	(270,2)	111,9	(318,7)	44,0	(59,1)	99,2	(246,1)
capital/empl. (1000€.p.w)	46,8	(59,7)	48,8	(60,3)	46,0	(63,3)	44,9	(58,2)
VA per worker (1000€.p.w)	51,9	(29,2)	49,6	(27,6)	52,8	(31,5)	53,9	(30,0)
average wage (1000€.p.w)	24,0	(6,7)	24,0	(6,7)	23,9	(6,7)	24,0	(6,6)
materials (% sales)	33,8	(18,3)	33,5	(18,1)	32,6	(18,3)	34,5	(18,5)
Customs data variables:								
fraction of exporters	69,0	(46,2)	70,8	(45,5)	61,9	(48,6)	69,0	(46,3)
fraction of importers	69,4	(46,1)	70,7	(45,5)	61,0	(48,8)	70,2	(45,8)
exports (% sales)	21,5	(25,8)	21,7	(25,6)	18,5	(24,1)	21,9	(26,3)
imports (% sales)	14,9	(16,9)	15,0	(16,7)	14,3	(17,0)	14,9	(17,1)
DADS-POSTES variables:								
number of workers (Nempl)	111,6	(299,9)	125	(352,7)	48,7	(64,1)	113,5	(274,5)
hiring rate (hr)	20,5	(17,2)	13,5	(12,5)	16,7	(14,0)	28,4	(18,6)
separation rate (sr)	19,8	(14,4)	22,2	(14,4)	16,6	(13,6)	18,2	(14,3)
average wage (1000€.p.w)	20,5	(5,7)	20,5	(5,6)	21,0	(5,8)	20,3	(5,7)
avg. log hourly wage (lsbrh x10)	24,2	(2,3)	24,2	(2,3)	24,2	(2,3)	24,2	(2,3)
hourly wage	12,7	(3,3)	12,7	(3,3)	12,7	(3,4)	12,7	(3,3)
hourly wage of new hires	10,8	(4,0)	11,1	(4,4)	10,4	(4,1)	10,6	(3,7)
hourly wage of separated	12,7	(5,2)	13,1	(5,2)	12,3	(5,4)	12,3	(5,2)
share of hours worked by								
– part time workers	4,7	(8,1)	4,9	(8,5)	4,6	(7,9)	4,5	(7,6)
– female workers	27,8	(23,7)	29,0	(24,1)	26,8	(24,2)	26,8	(23,1)
– senior staff and top managers	8,7	(10,2)	8,6	(10,0)	8,0	(10,3)	8,9	(10,5)
– supervisors	17,5	(12,8)	17,3	(12,4)	16,4	(13,2)	17,9	(13,1)
– clerical employees	8,3	(7,5)	8,2	(7,4)	8,7	(8,4)	8,3	(7,4)
– blue collar workers	63,7	(21,0)	64,2	(20,5)	64,5	(21,2)	63,1	(21,3)
– 26 to 32 year old workers	19,2	(10,5)	17,9	(10,2)	17,8	(10,9)	20,7	(10,6)
– 33 to 40 year old workers	25,1	(9,2)	25,0	(9,3)	25,3	(10,5)	25,2	(8,9)
– 41 to 48 year old workers	23,7	(9,6)	24,5	(9,4)	24,6	(10,7)	22,6	(9,3)
– 49+ year old workers	22,5	(12,7)	24,4	(12,9)	23,8	(13,7)	20,3	(11,9)
1995	7,6	(26,5)	6,7	(25,1)	7,7	(26,7)	8,5	(27,9)
1996	7,6	(26,5)	7,7	(26,6)	7,8	(26,9)	7,5	(26,4)
1997	7,9	(27,0)	7,5	(26,3)	8,2	(27,4)	8,3	(27,5)
1998	8,1	(27,2)	7,7	(26,7)	8,1	(27,3)	8,4	(27,7)
1999	7,9	(27,0)	8,0	(27,1)	8,1	(27,3)	7,9	(27,0)
2000	7,9	(26,9)	6,2	(24,2)	7,4	(26,1)	9,6	(29,4)
2001	7,9	(26,9)	8,2	(27,4)	7,0	(25,5)	7,8	(26,8)
2002	7,7	(26,6)	9,4	(29,2)	7,7	(26,6)	5,9	(23,6)
2003	7,5	(26,4)	8,9	(28,4)	8,3	(27,5)	6,1	(23,9)
2004	7,5	(26,3)	9,0	(28,6)	7,2	(25,8)	6,0	(23,7)
2005	7,8	(26,8)	8,0	(27,2)	8,3	(27,5)	7,4	(26,3)
2006	7,4	(26,1)	6,7	(25,0)	7,6	(26,5)	8,0	(27,1)
2007	7,3	(26,0)	6,0	(23,7)	6,7	(25,1)	8,7	(28,2)

Sources: DADS-Postes, customs data and EAE 1995-2007. The variable definitions are presented in the relevant subsections of the data appendix (section A). Standard deviations are in brackets. In a preliminary step, all ratio variables were winzored at the 1% level.

A.8.3 The firm-level aggregated EAE-Trade-Panel dataset

I construct a firm-level version of the EAE-Trade-Panel dataset by summing and averaging variables across sampled workers at the firm level. These variables are proxies for the EAE-Trade-Postes variables but the nature of the DADS panels allows me to refine some of them. Specifically, the full panel allows me to define the hiring rate of workers that are still employed at the same firm the following year ($\mathsf{hr}_{continued}$) and the separation rates of workers that were hired in the previous year or earlier (sr_{notnew}). For the other variables for which the definitions coincide, I verify that the Postes variables and the Panel proxies are closely related.

A.8.4 Descriptive statistics about the selected EAE-Trade-Panel sample

I report hours and average wages of workers by job category for the full sample of DADS-Panel workers and for the selected workers of the EAE-Trade-Panel subsample in tables 9 and 10 respectively. The fraction of new and terminated workers is smaller in the subsample because of the exclusion of the years in which firms that enter and exit the data, the exclusion of outliers and the selection of larger firms. The different average wages are higher in the subsample because wages are higher in the manufacturing industries, because the exclusion of firms with less than five sampled workers disproportionately affected small low-wage firms.

I compare the characteristics of the EAE-Trade-Postes and EAE-Trade-Panel samples in table 11. The first two columns of the table pertaining to the EAE-Trade-Postes are reproduced from the first two columns of table 8. Because of the selection of large firms that have at least five sampled workers, the firms in the EAE-Trade-Panel are on average larger, more productive, more engaged in international trade. They pay higher wages and experience smaller worker flows.

Table 9: Job flow characteristics in the initial full DADS-Panel dataset.

Panel A.	Inflows $(t-1,t)$				
	All jobs	Continued jobs	New jobs	Continued new jobs	Terminated new jobs
Number of jobs (millions)	11,50	8,74	2,76	1,60	1,16
	100%	76%	24%	58%	42%
Hours worked (billions)	16,03	13,86	2,17	1,51	0,66
	100%	87%	14%	70%	30%
Hourly wage	17,87	18,33	14,92	15,37	13,87
	(12,86)	(13,10)	(10,71)	(10,99)	(9,96)
Log hourly wage	2,75	2,78	2,57	2,59	2,50
	(0,50)	(0,49)	(0,52)	(0,52)	(0,50)
Avg. log residual wage (1)	0,00	0,01	-0,06	-0,07	-0,06
	(0,33)	(0,32)	(0,36)	(0,35)	(0,39)
Avg. log residual wage (2)	-0,01	-0,01	-0,02	-0,02	-0,02
	(0,32)	(0,32)	(0,36)	(0,35)	(0,38)

Panel B.	Outflows $(t,t+1)$				
	All jobs	Continued jobs	Terminated jobs	Terminated non-new jobs	Terminated new jobs
Number of jobs (millions)	11,50	8,58	2,92	1,76	1,16
	100%	75%	25%	60%	40%
Hours worked (billions)	16,03	13,66	2,37	1,71	0,66
	100%	85%	15%	72%	28%
Hourly wage	17,87	18,11	16,49	17,5	13,87
	(12,86)	(12,66)	(13,83)	(14,94)	(9,96)
Log hourly wage	2,75	2,77	2,64	2,69	2,50
	(0,50)	(0,48)	(0,56)	(0,57)	(0,50)
Avg. log residual wage (1)	0,00	0,00	-0,03	-0,02	-0,06
	(0,33)	(0,31)	(0,40)	(0,40)	(0,39)
Avg. log residual wage (2)	-0,01	-0,01	-0,03	-0,03	-0,02
	(0,32)	(0,31)	(0,40)	(0,40)	(0,38)

Sources: DADS-Panel 1995-2007. The variables, the averages and standard deviations are defined in the legend of table 6. Nevertheless, there is one difference with table 6. The values are computed on the subsample of observations that are in the DADS-Panel dataset as detailed in subsection A.2.

Table 10: Job flow characteristics in the selected EAE-Trade-Panel sample.

Panel A.	Inflows ($t-1$,t)				
	All jobs	Continued jobs	New jobs	Continued new jobs	Terminated new jobs
Number of jobs (thousands)	646,55	578,91	67,64	47,78	19,87
	100%	90%	11%	71%	29%
Hours worked (millions)	1076	1017	59,41	46,98	12,43
	100%	95%	6%	79%	21%
Hourly wage	19,83	20,02	16,68	17,19	14,74
	(12,57)	(12,56)	(12,26)	(12,21)	(12,23)
Log hourly wage	2,87	2,88	2,66	2,70	2,52
	(0,46)	(0,45)	(0,53)	(0,52)	(0,56)
Avg. log residual wage (1)	0,03	0,03	-0,07	-0,06	-0,10
	(0,28)	(0,28)	(0,36)	(0,33)	(0,45)
Avg. log residual wage (2)	0,02	0,02	-0,02	-0,01	-0,05
	(0,28)	(0,28)	(0,36)	(0,33)	(0,45)

Panel B.	Outflows (t,$t+1$)				
	All jobs	Continued jobs	Terminated jobs	Terminated non-new jobs	Terminated new jobs
Number of jobs (thousands)	646,55	570,01	76,54	56,68	19,87
	100%	88%	12%	74%	26%
Hours worked (millions)	1076	1004	72,36	59,94	12,43
	100%	93%	7%	83%	17%
Hourly wage	19,83	19,75	20,91	22,19	14,74
	(12,57)	(12,07)	(18,09)	(18,83)	(12,23)
Log hourly wage	2,87	2,87	2,83	2,90	2,52
	(0,46)	(0,44)	(0,63)	(0,62)	(0,56)
Avg. log residual wage (1)	0,03	0,03	0,01	0,03	-0,10
	(0,28)	(0,27)	(0,44)	(0,43)	(0,45)
Avg. log residual wage (2)	0,02	0,02	0,02	0,03	-0,05
	(0,28)	(0,27)	(0,44)	(0,43)	(0,45)

Sources: DADS-Panel 1995-2007. The variables, the averages and standard deviations are defined in the legend of table 6. Nevertheless, there is one difference with table 6. The values are computed on the subsample of observations that are in the EAE-Trade-Panel dataset as detailed in subsection A.8.

Table 11: Firm average characteristics in the EAE-Trade-Postes and -Panel samples.

	EAE-Trade-Postes		EAE-Trade-Panel	
number of firms	33 897		9 470	
number of observations	209 264		45 980	
EAE variables:				
sales (1000,000€)	18,4	(88,8)	61,4	(180,4)
employment	98,9	(270,2)	297,2	(528,6)
capital/empl. (1000€.p.w)	46,8	(59,7)	67,2	(72,6)
VA per worker (1000€.p.w)	51,9	(29,2)	57,4	(31,4)
average wage (1000€.p.w)	24,0	(6,7)	25,2	(7,0)
materials (% sales)	33,8	(18,3)	37,8	(18,1)
Customs data variables:				
fraction of exporters	69,0	(46,2)	88,4	(32,0)
fraction of importers	69,4	(46,1)	91,2	(28,3)
exports (% sales)	21,5	(25,8)	28,5	(27,9)
imports (% sales)	14,9	(16,9)	16,9	(16,9)
DADS-POSTES variables:				
number of workers (Nempl)	111,6	(299,9)	333,7	(585,6)
hiring rate (hr)	20,5	(17,2)	18,0	(15,2)
separation rate (sr)	19,8	(14,4)	17,5	(12,4)
average wage (1000€.p.w)	20,5	(5,7)	21,7	(5,8)
avg. log hourly wage (lsbrh x10)	24,2	(2,3)	24,8	(2,4)
hourly wage	12,7	(3,3)	13,4	(3,5)
hourly wage of new hires	10,8	(4,0)	12,0	(4,2)
hourly wage of separated	12,7	(5,2)	14,5	(5,4)
share of hours worked by				
– part time workers	4,7	(8,1)	4,9	(9,1)
– female workers	27,8	(23,7)	29,9	(22,3)
– senior staff and top managers	8,7	(10,2)	10,8	(11,0)
– supervisors	17,5	(12,8)	19,7	(11,8)
– clerical employees	8,3	(7,5)	7,7	(6,0)
– blue collar workers	63,7	(21,0)	61,3	(20,6)
– 26 to 32 year old workers	19,2	(10,5)	19,3	(9,1)
– 33 to 40 year old workers	25,1	(9,2)	25,1	(7,3)
– 41 to 48 year old workers	23,7	(9,6)	24,2	(7,8)
– 49+ year old workers	22,5	(12,7)	22,9	(11,3)
1995	7,6	(26,5)	8,0	(27,2)
1996	7,6	(26,5)	7,7	(26,6)
1997	7,9	(27,0)	7,8	(26,8)
1998	8,1	(27,2)	8,1	(27,3)
1999	7,9	(27,0)	8,0	(27,1)
2000	7,9	(26,9)	8,2	(27,4)
2001	7,9	(26,9)	8,3	(27,6)
2002	7,7	(26,6)	7,5	(26,3)
2003	7,5	(26,4)	7,1	(25,7)
2004	7,5	(26,3)	7,3	(26,0)
2005	7,8	(26,8)	7,2	(25,9)
2006	7,4	(26,1)	7,4	(26,1)
2007	7,3	(26,0)	7,5	(26,3)

Sources: DADS-Postes and -Panel, customs data and EAE 1995-2007. The variable definitions are presented in the relevant subsections of the data appendix (section A). Standard deviations are in brackets. In a preliminary step, all ratio variables were winzored at the 1% level.

A.8.5 The effect of time varying variables on wages

Estimate the effect of time-varying worker characteristics control for job effects:

$$\mathsf{lsbrh}_{i,t} = \beta X_{i,t} + \gamma_{i,j(i,t)} + \epsilon_{i,t} \tag{16}$$

where $j(i,t)$ represent the firm j that employs worker i at date t. The time-varying worker characteristics include a dummy for working part-time, a polynomial of order four in labor market experience, a polynomial of order four in tenure at the current job, year effects, indicators of the number of quarters worked in the current year, indicators of promotions and demotions, a dummy for being a resident of the Paris area. The firm level controls include the firm average log hourly wage which is set to zero if missing and associated to an indicators of missing values (8% of observations), a dummy for importing firms, firm log imports, log revenues, log input purchases, log capital-employment ratio and investment rate which are all set to zero when missing and the corresponding indicator for missing values (36% observations - 5% in common with the other indicator)[56].

I report the coefficient estimates in table 12.

[56] In a preliminary step, I set to missing the values of the inconsistent observations (4.6% of all observations) (see subsection A.7.2 for more details).

Table 12: The effect of time-varying worker characteristics on log hourly wages.

	log hourly wage	
labor market experience		
– square	-0.295***	(0.004)
– cubic	0.052***	(0.001)
– quadratic	-0.004***	(0.000)
tenure		
– square	-0.286***	(0.003)
– cubic	0.119***	(0.001)
– quadratic	-0.016***	(0.000)
part-time dummy	0.102***	(0.001)
IDF dummy	0.014***	(0.002)
less than a full quarter worked dummy	0.135***	(0.001)
1 full quarter worked dummy	0.058***	(0.001)
2 full quarters worked dummy	0.050***	(0.001)
3 full quarter worked dummy	0.035***	(0.001)
supervisor promotion dummy	0.084***	(0.001)
clerical worker promotion dummy	0.036***	(0.002)
blue collar worker promotion dummy	0.043***	(0.001)
senior staff demotion dummy	-0.142***	(0.001)
supervisor demotion dummy	-0.041***	(0.001)
blue collar worker demotion dummy	-0.031***	(0.003)
firm variables:		
firm average log hourly wage	0.496***	(0.002)
missing log hourly wage dummy	1.450***	(0.029)
log sales	0.002***	(0.000)
log capital intensity	-0.004***	(0.000)
log material expenditure	0.003***	(0.000)
investment rate	0.000	(0.000)
missing EAE variable dummy	0.030***	(0.003)
importing firm dummy	-0.037***	(0.002)
imports	0.004***	(0.000)
Observations	1,759,009	
R-squared	0.291	

Sources: EAE-Trade-Panel 1995-2007. The regression includes match fixed effects and year effects. In a preliminary steps, all variables were deviated from the match average following Woodstock (2007).[40] Standard errors are in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

B Full regression tables and robustness checks

Table 13: The effect of firm growth on separation rates in EAE-Trade-Postes.

Dependent variable: the separation rate	(13.A) Basic	(13.B) Firm effects	(13.C) Weights & controls	(13.D) Single establishment	(13.E) Revenue growth	(13.F) Smoothed growth
max(0,growth rate)	0.394***	0.116***	0.122***	0.077***	0.033***	0.081***
	(0.008)	(0.006)	(0.009)	(0.007)	(0.004)	(0.007)
min(growth rate,0)	-0.992***	-0.749***	-0.839***	-0.719***	-0.072***	-0.563***
	(0.006)	(0.005)	(0.007)	(0.009)	(0.008)	(0.019)
Workforce characteristics:						
incumbents' wage			0.026***	0.049***	0.019**	0.025***
			(0.006)	(0.007)	(0.009)	(0.008)
average experience (x10)			-0.112***	-0.127***	-0.087***	-0.105***
			(0.004)	(0.005)	(0.006)	(0.005)
share of hours worked by						
– part time workers			0.005	0.005	0.011	0.009
			(0.006)	(0.009)	(0.008)	(0.008)
– female workers			0.084***	0.097***	0.091***	0.092***
			(0.015)	(0.014)	(0.021)	(0.018)
– senior staff			0.088***	0.091***	0.049	0.092***
			(0.025)	(0.026)	(0.030)	(0.028)
– supervisors			0.088***	0.123***	0.050	0.089***
			(0.026)	(0.026)	(0.031)	(0.030)
– clerical employees			0.135***	0.135***	0.114***	0.140***
			(0.033)	(0.029)	(0.038)	(0.037)
– blue collar workers			0.138***	0.184***	0.098***	0.141***
			(0.026)	(0.027)	(0.031)	(0.030)
Other firm characteristics:						
log revenues			-0.004*	-0.009***		-0.009***
			(0.002)	(0.003)		(0.003)
log capital intensity			-0.003**	-0.003*		-0.000
			(0.001)	(0.002)		(0.001)
log materials			0.004***	0.004***		0.005***
			(0.001)	(0.001)		(0.001)
investment rate			0.000***	0.000***		0.000***
			(0.000)	(0.000)		(0.000)
export dummy			0.004	0.003	0.011**	0.002
			(0.004)	(0.004)	(0.005)	(0.005)
import dummy			-0.004	-0.002	0.020***	0.007
			(0.005)	(0.006)	(0.007)	(0.006)
log exports			-0.000	-0.000	-0.001	-0.000
– (0 if none)			(0.000)	(0.000)	(0.000)	(0.000)
log imports			0.000	0.000	-0.002***	-0.001
– (0 if none)			(0.000)	(0.001)	(0.001)	(0.001)
Firm effects	NO	YES	YES	YES	YES	YES
Weights	NO	NO	Njob	Njob	Njob	Njob
Observations	209,264	204,264	187,896	143,972	189,132	187,896
R-squared	0.179	0.617	0.691	0.667	0.563	0.588

Sources: EAE-Trade-Postes 1995-2007. Estimates of the regression specified in equation (1). In column A, estimates are from a simple OLS regression with year effects but no controls. Firms effects are included in B-F and controls in C-F. Also in C-F, observations are weighted by the number of jobs. In D, the sample is restricted to single-establishment firms. Revenue growth is used instead of job growth in E. A three year moving average of the growth rate in the average number of jobs is used in F. Firm-level clustered standard errors are in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 14: The effect of firm growth on separation rates in EAE-Trade-Panel.

Dependent variable: the separation rate	(14.A) Postes variable	(14.B) Panel proxy	(14.C) Panel non-hire separations
max(0,growth rate)	0.139***	0.087***	-0.009
	(0.016)	(0.014)	(0.010)
min(growth rate,0)	-0.883***	-0.534***	-0.535***
	(0.011)	(0.023)	(0.021)
Workforce characteristics:			
incumbents' wage	0.011	0.031**	0.014
	(0.010)	(0.012)	(0.009)
average experience (x10)	-0.105***	-0.073***	-0.026***
	(0.007)	(0.008)	(0.006)
share of hours worked by			
– part time workers	0.006	-0.003	-0.006
	(0.008)	(0.007)	(0.007)
– female workers	0.096***	0.098***	0.022
	(0.030)	(0.035)	(0.025)
– senior staff	0.021	0.101*	0.061
	(0.032)	(0.056)	(0.041)
– supervisors	0.029	0.128**	0.072*
	(0.032)	(0.056)	(0.041)
– clerical employees	0.029	0.121**	0.063
	(0.033)	(0.057)	(0.042)
– blue collar workers	0.014	0.136**	0.060
	(0.031)	(0.056)	(0.041)
Other firm characteristics:			
log revenues	-0.001	-0.009**	-0.007**
	(0.004)	(0.004)	(0.003)
log capital intensity	-0.002	-0.001	0.000
	(0.002)	(0.002)	(0.001)
log materials	0.004**	0.003*	0.002
	(0.002)	(0.002)	(0.001)
investment rate	0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)
export dummy	0.007	-0.000	-0.001
	(0.007)	(0.010)	(0.008)
import dummy	-0.001	0.001	-0.001
	(0.014)	(0.014)	(0.011)
log exports	-0.001	-0.000	0.000
– (0 if none)	(0.001)	(0.001)	(0.001)
log imports	0.001	-0.000	0.000
– (0 if none)	(0.001)	(0.001)	(0.001)
Firm effects, year effects	YES	YES	YES
Weights	Njob	Njob	Njob
Observations	44,318	44,318	44,318
R-squared	0.774	0.534	0.431

Sources: EAE-Trade-Panel 1995-2007. All specifications follow equation (1). In column A, the specification in (13.C) is implemented on the EAE-Trade-Panel subsample using the EAE-Trade-Postes variable for the separation rate. In B, the separation rate used is the EAE-Trade-Panel proxy. In C, the separation rate is computed as the ratio of separations of non-new hires to the average number of jobs. Firm-level clustered standard errors are in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 15: Change in the average characteristics of new hires with firm growth.

	(15.A)	(15.B)	(15.C)	(15.D)	(15.E)	(15.F)
	new hire avg. exp-rience (x10)	Share of hours worked by new hires of part-time workers	senior staff	supervisors	clerical workers	blue collar workers
max(0,growth rate)	0.584***	-0.021***	-0.024***	0.014*	-0.024***	0.034***
	(0.024)	(0.005)	(0.006)	(0.008)	(0.004)	(0.009)
min(growth rate,0)	-0.345***	-0.030***	-0.022***	-0.036***	-0.021***	0.083***
	(0.031)	(0.006)	(0.008)	(0.010)	(0.006)	(0.012)
Workforce characteristics:						
average experience (x10)	0.999***	0.027***	0.040***	0.035***	0.007**	-0.089***
	(0.026)	(0.003)	(0.004)	(0.004)	(0.003)	(0.006)
share of hours worked by						
– part time workers	0.023	0.807***	-0.012*	-0.005	0.004	0.015
	(0.028)	(0.019)	(0.007)	(0.007)	(0.005)	(0.009)
– female workers	0.138**	-0.001	-0.014	0.020	-0.001	-0.006
	(0.067)	(0.013)	(0.018)	(0.015)	(0.011)	(0.023)
– senior staff	0.189	-0.036	0.863***	0.012	-0.063**	-0.279***
	(0.124)	(0.029)	(0.037)	(0.038)	(0.030)	(0.057)
– supervisors	0.286**	-0.047	-0.032	0.876***	-0.057*	-0.256***
	(0.127)	(0.029)	(0.034)	(0.038)	(0.031)	(0.056)
– clerical employees	0.244	-0.041	-0.070*	-0.065	0.998***	-0.332***
	(0.150)	(0.032)	(0.036)	(0.040)	(0.039)	(0.062)
– blue collar workers	0.175	-0.046	-0.083**	-0.050	-0.072**	0.738***
	(0.125)	(0.029)	(0.033)	(0.037)	(0.030)	(0.056)
Other firm characteristics:						
log revenues	-0.021*	-0.004*	-0.008**	-0.002	0.003*	0.007*
	(0.011)	(0.002)	(0.003)	(0.003)	(0.001)	(0.004)
log capital intensity	0.008	0.000	0.004***	0.002	0.000	-0.006**
	(0.006)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
log materials	0.003	-0.000	0.002	-0.000	0.000	-0.001
	(0.004)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
investment rate	-0.000***	-0.000***	0.000***	-0.000***	0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
export dummy	-0.011	-0.002	-0.005	0.001	0.000	0.003
	(0.025)	(0.004)	(0.005)	(0.006)	(0.004)	(0.008)
import dummy	0.034	0.004	0.002	0.004	0.005	-0.011
	(0.028)	(0.006)	(0.008)	(0.010)	(0.004)	(0.010)
log exports	0.001	0.000	0.001	-0.000	-0.000	-0.000
– (0 if none)	(0.002)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
log imports	-0.003	-0.001	-0.000	-0.000	-0.000	0.001
– (0 if none)	(0.003)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Firm effects, year effects	YES	YES	YES	YES	YES	YES
Weights	Nin	Nin	Nin	Nin	Nin	Nin
Observations	181,704	181,704	181,704	181,704	181,704	181,704
R-squared	0.603	0.624	0.782	0.631	0.610	0.772

Sources: EAE-Trade-Postes 1995-2007. Specifications follow equation (1) with average characteristics of new hires as the dependent variables. The regressions are weighted by the number of new hires. Firm-level clustered standard errors are in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 16: Change in the average characteristics of separated workers with firm growth.

	(16.A)	(16.B)	(16.C)	(16.D)	(16.E)	(16.F)
	separated avg experience (x10)	Share of hours worked by separated workers of female workers	senior staff	supervisors	clerical workers	blue collar workers
max(0,growth rate)	-0.003	-0.008	0.007	0.031***	0.004	-0.045***
	(0.147)	(0.006)	(0.008)	(0.008)	(0.004)	(0.010)
min(growth rate,0)	-0.667***	0.004	0.032***	0.015	0.001	-0.050***
	(0.160)	(0.008)	(0.010)	(0.009)	(0.006)	(0.013)
Workforce characteristics:						
average experience (x10)	0.378***	0.008*	0.000	0.006	0.012***	-0.020***
	(0.023)	(0.004)	(0.004)	(0.004)	(0.003)	(0.006)
share of hours worked by						
– part time workers	-0.009	0.001	0.006	0.004	0.003	-0.013
	(0.036)	(0.006)	(0.012)	(0.011)	(0.007)	(0.012)
– female workers	0.072	0.138***	-0.009	-0.006	-0.104***	0.120***
	(0.067)	(0.025)	(0.017)	(0.017)	(0.013)	(0.024)
– senior staff	0.973***	-0.135***	0.449***	0.101**	-0.017	-0.773***
	(0.176)	(0.043)	(0.038)	(0.042)	(0.031)	(0.058)
– supervisors	1.096***	-0.156***	0.031	0.465***	0.003	-0.741***
	(0.174)	(0.044)	(0.035)	(0.042)	(0.032)	(0.056)
– clerical employees	1.148***	-0.202***	-0.031	0.065	0.437***	-0.716***
	(0.179)	(0.047)	(0.039)	(0.043)	(0.051)	(0.065)
– blue collar workers	0.979***	-0.129***	0.042	0.093**	0.007	-0.385***
	(0.172)	(0.043)	(0.035)	(0.040)	(0.032)	(0.055)
Other firm characteristics:						
log revenues	-0.087***	0.005*	-0.002	-0.008***	0.002	0.010**
	(0.013)	(0.003)	(0.003)	(0.003)	(0.002)	(0.004)
log capital intensity	0.024**	0.000	0.001	0.001	0.000	-0.003
	(0.009)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
log materials	0.014*	-0.001	0.001	0.001	-0.001	-0.001
	(0.008)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
investment rate	-0.000***	0.000***	-0.000	-0.000*	0.000***	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
export dummy	-0.019	0.005	-0.001	0.008	0.003	-0.009
	(0.027)	(0.006)	(0.005)	(0.007)	(0.004)	(0.009)
import dummy	-0.060*	-0.005	-0.003	-0.005	-0.006	0.017*
	(0.033)	(0.007)	(0.007)	(0.008)	(0.005)	(0.009)
log exports	0.001	-0.000	0.000	-0.001	-0.000	0.001
– (0 if none)	(0.003)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
log imports	0.005*	0.001	0.000	0.000	0.001	-0.001
– (0 if none)	(0.003)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Firm effects, year effects	YES	YES	YES	YES	YES	YES
Weights	Nou	Nou	Nou	Nou	Nou	Nou
Observations	182,611	182,611	182,611	182,611	182,611	182,611
R-squared	0.598	0.797	0.727	0.556	0.524	0.735

Sources: EAE-Trade-Postes 1995-2007. Specifications follow equation (1) with average characteristics of separated workers as the dependent variables. The regressions are weighted by the number of separated workers. Firm-level clustered standard errors are in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 17: Change in the characteristics of new and separated workers with firm growth.

	(17.A)	(17.B)	(17.C)	(17.D)	(17.E)	(17.F)
	New workers			Separated workers		
	Share of hours by		average	Share of hours by		average
	part-time workers	job-to-job transitions	job spell	part-time workers	job-to-job transitions	job spell
max(0,growth rate)	-0.015	1.389***	0.224***	-0.051	-0.579	0.081*
	(0.018)	(0.258)	(0.051)	(0.031)	(0.893)	(0.046)
min(growth rate,0)	-0.043	1.272***	0.063	0.135***	-5.967***	-0.591***
	(0.045)	(0.417)	(0.071)	(0.035)	(0.965)	(0.081)
Workforce characteristics:						
average experience (x10)	0.010	0.617**	0.000	0.037	5.121***	0.000
	(0.019)	(0.276)	(0.004)	(0.025)	(0.735)	(0.004)
share of hours worked by						
– part time workers	0.767***	-0.075	0.021	0.784***	0.700	0.080
	(0.044)	(0.283)	(0.056)	(0.049)	(0.807)	(0.057)
– female workers	-0.057	-0.355	-0.345**	0.051	-5.293**	-0.227
	(0.077)	(0.968)	(0.164)	(0.093)	(2.483)	(0.144)
– senior staff	-0.125	-4.777	1.014	0.620	-2.320	0.628
	(0.431)	(5.384)	(0.821)	(0.491)	(13.664)	(0.710)
– supervisors	-0.102	-6.220	1.290	0.482	-2.314	0.670
	(0.431)	(5.304)	(0.815)	(0.476)	(13.744)	(0.713)
– clerical employees	-0.078	-6.406	1.098	0.494	-3.515	0.582
	(0.437)	(5.313)	(0.823)	(0.479)	(13.805)	(0.716)
– blue collar workers	-0.126	-6.952	1.194	0.510	-2.051	0.520
	(0.436)	(5.320)	(0.815)	(0.475)	(13.911)	(0.709)
Other firm characteristics:						
log revenues	0.002	-0.379***	0.007	-0.002	-1.082***	-0.010
	(0.010)	(0.120)	(0.020)	(0.011)	(0.325)	(0.018)
log capital intensity	0.006	-0.017	-0.015	0.007	0.159	-0.001
	(0.004)	(0.067)	(0.012)	(0.005)	(0.157)	(0.012)
log materials	0.001	0.006	0.009	0.005	0.024	0.007
	(0.004)	(0.055)	(0.012)	(0.006)	(0.140)	(0.007)
investment rate	0.000***	-0.000***	-0.000***	0.001	0.021	-0.005
	(0.000)	(0.000)	(0.000)	(0.002)	(0.027)	(0.004)
export dummy	0.012	-0.399	0.016	-0.012	0.048	0.021
	(0.030)	(0.330)	(0.058)	(0.044)	(0.969)	(0.057)
import dummy	0.010	0.006	-0.050	0.062	-0.807	0.015
	(0.036)	(0.447)	(0.072)	(0.067)	(1.345)	(0.065)
log exports	-0.001	0.039	0.000	0.001	-0.023	0.002
– (0 if none)	(0.003)	(0.030)	(0.005)	(0.004)	(0.081)	(0.005)
log imports	-0.002	0.007	0.006	-0.004	0.050	-0.000
– (0 if none)	(0.003)	(0.039)	(0.006)	(0.004)	(0.109)	(0.005)
Firm effects, year effects	YES	YES	YES	YES	YES	YES
Weights	Nin	Nin	Nin	Nou	Nou	Nou
Observations	26,191	26,191	26,191	28,46	28,46	28,46
R-squared	0.456	0.572	0.396	0.418	0.529	0.344

Sources: EAE-Trade-Panel 1995-2007. Specifications follow equation (1) with average characteristics of new or separated workers as the dependent variable. The regressions are weighted by the number of new (Nin) or separated workers (Nou). Firm-level clustered standard errors are in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 18: Wage elasticity of new hires with respect to firm growth.

	(18.A) log hourly wage	(18.B) residual log wage	(18.C) single-establishment	(18.D) Revenue growth	(18.E) Smoothed growth	(18.F) residual log wage
max(0,growth rate)	0.124***	0.067***	0.032***	0.021***	0.013***	
	(0.014)	(0.012)	(0.009)	(0.006)	(0.004)	
min(growth rate,0)	-0.133***	-0.050***	-0.061***	-0.023**	-0.030	
	(0.016)	(0.011)	(0.009)	(0.010)	(0.019)	
log hiring rate						0.019***
						(0.002)
Workforce characteristics						
incumbents' wage	0.269***	0.576***	0.563***	0.581***	0.581***	0.036*
	(0.018)	(0.012)	(0.011)	(0.012)	(0.012)	(0.021)
average experience (x10)	0.145***	0.016**	-0.000	0.014**	0.014**	-0.001
	(0.010)	(0.007)	(0.006)	(0.007)	(0.007)	(0.010)
share of hours worked by						
– part time workers	0.056***	0.000	0.015	0.001	0.001	0.033
	(0.015)	(0.011)	(0.013)	(0.011)	(0.011)	(0.043)
– female workers	-0.070**	0.044**	0.032*	0.053**	0.052**	0.030***
	(0.033)	(0.021)	(0.018)	(0.023)	(0.023)	(0.007)
– senior staff	0.146**	0.036	0.069	0.029	0.029	0.105**
	(0.062)	(0.043)	(0.047)	(0.046)	(0.046)	(0.043)
– supervisors	-0.022	0.105**	0.077*	0.102**	0.102**	0.158***
	(0.060)	(0.044)	(0.046)	(0.046)	(0.046)	(0.051)
– clerical employees	-0.134**	0.160***	0.121**	0.155***	0.155***	0.132***
	(0.063)	(0.051)	(0.048)	(0.053)	(0.053)	(0.043)
– blue collar workers	-0.281***	0.136***	0.092**	0.130***	0.131***	-0.003
	(0.059)	(0.043)	(0.046)	(0.046)	(0.046)	(0.003)
Other firm characteristics:						
log revenues	-0.000	-0.002	0.001	-0.004	-0.003	-0.001
	(0.006)	(0.003)	(0.003)	(0.004)	(0.004)	(0.002)
log capital intensity	0.007**	-0.001	-0.002	-0.003	-0.003	0.006***
	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
log materials	0.006**	0.006***	0.003	0.006***	0.006***	0.000***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)
investment rate	-0.000***	0.000***	0.000***	0.000	0.000	0.006
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.008)
export dummy	0.001	0.006	0.008	0.007	0.008	-0.000
	(0.012)	(0.008)	(0.008)	(0.008)	(0.008)	(0.001)
import dummy	0.018	0.016	0.007	0.016	0.017	-0.002
	(0.013)	(0.011)	(0.007)	(0.012)	(0.012)	(0.001)
log exports	-0.000	-0.001	-0.001	-0.001	-0.001	0.017
– (0 if none)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.012)
log imports	-0.001	-0.001	-0.001	-0.001	-0.001	0.576***
– (0 if none)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.012)
Firm effects, year effects	YES	YES	YES	YES	YES	YES
Weights	Nin	Nin	Nin	Nin	Nin	Nin
Observations	181,704	181,704	143,576	169,496	169,496	181,704
R-squared	0.812	0.637	0.605	0.637	0.637	0.639

Sources: EAE-Trade-Postes 1995-2007. Specifications follow equation (1) with average wages of new workers as the dependent variable. The log hourly wage is used in column A while the residual log hourly wage obtained from equation (2) is used in the rest of the table. The regressions are weighted by the number of new workers (Nin). Firm-level clustered standard errors are in parentheses; *** p<0.01, ** p<0.05, * p<0.1. An excerpt is available in table (4) in the main text.

Table 19: Wage elasticity of separated workers with respect to firm growth.

	(19.A) log hourly wage	(19.B) residual log wage	(19.C) single-establishment	(19.D) Revenue growth	(19.E) Smoothed growth	(19.F) residual log wage
max(0,growth rate)	-0.007	0.003	-0.002	0.004	0.001	
	(0.014)	(0.010)	(0.007)	(0.005)	(0.002)	
min(growth rate,0)	-0.215***	-0.118***	-0.127***	-0.078***	-0.159***	
	(0.024)	(0.017)	(0.013)	(0.013)	(0.033)	
log separation rate						0.013***
						(0.002)
Workforce characteristics						
incumbents' wage	0.364***	0.683***	0.694***	0.684***	0.686***	0.685***
	(0.020)	(0.015)	(0.014)	(0.015)	(0.015)	(0.015)
average experience (x10)	0.138***	0.011	-0.000	0.016	0.014	0.022**
	(0.013)	(0.010)	(0.008)	(0.010)	(0.010)	(0.010)
share of hours worked by						
– part time workers	0.015	-0.030***	-0.021	-0.034***	-0.035***	-0.031***
	(0.015)	(0.011)	(0.013)	(0.011)	(0.011)	(0.011)
– female workers	-0.186***	-0.035	-0.036*	-0.033	-0.033	-0.039
	(0.033)	(0.026)	(0.019)	(0.027)	(0.027)	(0.026)
– senior staff	-0.258***	-0.155***	-0.154***	-0.202***	-0.194***	-0.157***
	(0.073)	(0.048)	(0.054)	(0.052)	(0.052)	(0.048)
– supervisors	-0.472***	-0.139***	-0.191***	-0.178***	-0.171***	-0.140***
	(0.072)	(0.048)	(0.053)	(0.051)	(0.051)	(0.048)
– clerical employees	-0.568***	-0.087*	-0.209***	-0.125**	-0.119**	-0.091*
	(0.080)	(0.053)	(0.055)	(0.056)	(0.056)	(0.053)
– blue collar workers	-0.761***	-0.194***	-0.229***	-0.236***	-0.229***	-0.198***
	(0.072)	(0.047)	(0.053)	(0.050)	(0.050)	(0.047)
Other firm characteristics:						
log revenues	-0.013**	-0.017***	-0.011**	-0.007	-0.009*	-0.017***
	(0.006)	(0.004)	(0.005)	(0.005)	(0.005)	(0.004)
log capital intensity	0.012***	0.007**	0.002	0.008**	0.008**	0.007**
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)
log materials	0.002	0.003	-0.002	0.002	0.003	0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
investment rate	-0.000	0.000	0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
export dummy	-0.006	0.002	0.002	0.001	-0.000	0.001
	(0.011)	(0.008)	(0.009)	(0.009)	(0.009)	(0.008)
import dummy	0.006	0.012	0.019*	0.018	0.014	0.014
	(0.015)	(0.012)	(0.010)	(0.013)	(0.012)	(0.012)
log exports	0.001	0.000	0.000	0.000	0.000	0.000
– (0 if none)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
log imports	-0.001	-0.002	-0.002**	-0.002*	-0.002	-0.002*
– (0 if none)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Firm effects, year effects	YES	YES	YES	YES	YES	YES
Weights	Nou	Nou	Nou	Nou	Nou	Nou
Observations	179,852	179,852	141,792	168,243	168,243	179,852
R-squared	0.791	0.608	0.575	0.608	0.609	0.607

Sources: EAE-Trade-Postes 1995-2007. Specifications follow equation (1) with average wages of separated workers as the dependent variable. The log hourly wage is used in column A while the residual log hourly wage obtained from equation (2) is used in the rest of the table. The regressions are weighted by the number of separated workers (Nou). Firm-level clustered standard errors are in parentheses; *** p<0.01, ** p<0.05, * p<0.1. An excerpt is available in table (4) in the main text.

Table 20: Hiring wage elasticity to firm growth: controlling for unobserved heterogeneity.

	(20.A)	(20.B)	(20.C)
	Firm average	Individual	
	residual log wage	log hourly wage	log hourly wage
log hiring rate (0 if unknown)	0.023***	0.026***	0.025***
– (at the hiring date)	(0.003)	(0.003)	(0.003)
dummy for unknown hiring rate		-0.030***	-0.023***
– (at the hiring date)		(0.006)	(0.006)
job-to-job transition dummy			0.042***
			(0.002)
Individual variable characteristics:			
tenure		0.384***	0.192***
		(0.016)	(0.014)
– square		-0.325***	-0.208***
		(0.012)	(0.010)
– cubic		0.113***	0.085***
		(0.005)	(0.004)
– quadratic		-0.014***	-0.011***
		(0.001)	(0.001)
labor market experience (x10)		-0.005	0.746***
		(0.261)	(0.267)
– square			-0.202***
			(0.038)
– cubic			0.017
			(0.010)
– quadratic			0.001
			(0.001)
Firm characteristics:			
firm average residual wage	0.632***	0.670***	0.516***
	(0.022)	(0.022)	(0.102)
other firm controls	YES	YES	NO
Weights	Nin	NO	NO
Firm effects	YES	YES	YES
Year effects	YES	YES	YES
Worker effects	NO	YES	YES
Cohort effects	NO	YES	YES
Observations	44,146	1,585,440	1,730,197
R-squared	0.722	0.845	0.844

Sources: EAE-Trade-Postes 1995-2007. In the first column, the firm average residual log hourly wage defined in section 4.1 is regressed on the firm log hiring rate with firm and year effects. In the last two columns, regressions are at the individual level with firm, worker, year and cohort effects. Cohorts correspond to the first year of appearance in sample. Individual log hourly wages are regressed on the log hiring rate *at the time of hiring*. The latter variable is set to zero if unknown. For all columns, the firm characteristics used as controls are the same as in the specification of table 15. Firm-level clustered standard errors are in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 21: The causal effect of firm growth on the wage of new hires.

	(21.A)	(21.B)	(21.C)	(21.D)	(21.E)	(21.F)
					Single establishments	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
max(0,growth rate)	0.081***	0.675*				
	(0.017)	(0.384)				
min(growth rate,0)	-0.054***	-1.098				
	(0.013)	(1.015)				
log hiring rate			0.021***	0.104**	0.012***	0.100
			(0.002)	(0.047)	(0.002)	(0.114)
Workforce characteristics:						
average experience (x10)	0.020**	0.031	0.035***	0.109**	0.008	0.090
share of hours worked by	(0.009)	(0.037)	(0.010)	(0.043)	(0.007)	(0.106)
– part time workers	0.005	0.014	0.004	0.007	0.011	0.011
	(0.012)	(0.022)	(0.012)	(0.012)	(0.015)	(0.013)
– female workers	0.057*	0.053	0.049*	0.013	0.028	-0.003
	(0.030)	(0.047)	(0.030)	(0.040)	(0.028)	(0.054)
– senior staff	0.069	0.087	0.068	0.070	0.125	0.103
	(0.069)	(0.088)	(0.069)	(0.075)	(0.080)	(0.083)
– supervisors	0.148**	0.159*	0.152**	0.165**	0.127	0.118
	(0.069)	(0.093)	(0.069)	(0.076)	(0.079)	(0.078)
– clerical employees	0.198**	0.169	0.198**	0.186**	0.186**	0.167**
	(0.079)	(0.118)	(0.079)	(0.095)	(0.082)	(0.084)
– blue collar workers	0.175**	0.191**	0.173**	0.163**	0.127	0.074
	(0.068)	(0.091)	(0.068)	(0.074)	(0.078)	(0.100)
Other firm characteristics:						
average incumbents' wage	0.580***	0.551***	0.578***	0.562***	0.563***	0.538***
	(0.015)	(0.026)	(0.015)	(0.018)	(0.015)	(0.035)
log revenues	-0.008*	0.014	-0.009**	-0.008*	-0.008	-0.006
	(0.005)	(0.019)	(0.004)	(0.005)	(0.006)	(0.007)
log capital intensity	-0.001	0.006	-0.001	0.006	-0.004	0.002
	(0.003)	(0.011)	(0.003)	(0.006)	(0.004)	(0.009)
log materials	0.009***	0.002	0.009***	0.003	0.007**	0.001
	(0.003)	(0.007)	(0.003)	(0.004)	(0.004)	(0.009)
investment rate	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
import dummy	0.030**	0.001	0.034**	0.046***	0.011	0.030
	(0.014)	(0.036)	(0.016)	(0.015)	(0.010)	(0.027)
lag import dummy	-0.009	-0.018	-0.014	-0.052*	-0.010	-0.047
	(0.012)	(0.052)	(0.013)	(0.027)	(0.008)	(0.049)
log imports	-0.001	0.002	-0.001	0.001	0.000	0.002
– (0 if none)	(0.002)	(0.004)	(0.002)	(0.002)	(0.001)	(0.003)
lag log imports	-0.001	-0.002	-0.002	-0.006**	-0.001	-0.005
– (0 if none)	(0.001)	(0.005)	(0.001)	(0.003)	(0.001)	(0.005)
Observations	105,133	105,133	105,133	105,133	76,578	76,578
R-squared	0.647	0.476	0.649	0.591	0.607	0.545
Under-identification p-value		0,107		0,001		0,098
Maximum remaining bias		<15%		<10%		>25%
Instrument validity J-test				0,222		0,261

Sources: EAE-Trade-Postes 1995-2007. Specifications follow equations (9)-(10). In columns B, the job growth rates are instrumented as reported in (22.B1) and (22.B2). In columns D and F, the log hiring rate is instrumented as reported in (22.D) and (22.F). The regressions include firm and year effects and are weighted by the number of new workers (Nin). Firm-level clustered standard errors are in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 22: First stage regressions: the effect of foreign demand on firm growth.

	(22.B1) max(0,growth rate)	(22.B2) min(growth rate,0)	(22.D) log hiring rate	(22.F) single establishment log hiring rate
max(0,FDgr)	0.210***	-0.025	1.426***	0.510*
	(0.077)	(0.036)	(0.415)	(0.272)
min(FDgr,0)	0.002	0.152*	0.193	0.271
	(0.147)	(0.086)	(0.798)	(0.712)
Workforce characteristics:				
average experience (x10)	-0.068***	-0.028***	-0.890***	-0.932***
	(0.008)	(0.005)	(0.061)	(0.065)
share of hours worked by				
– part time workers	-0.027	-0.007	-0.029	-0.005
	(0.017)	(0.006)	(0.061)	(0.090)
– female workers	0.014	0.005	0.418**	0.352*
	(0.045)	(0.017)	(0.174)	(0.205)
– senior staff	-0.005	0.012	0.012	0.256
	(0.088)	(0.031)	(0.358)	(0.294)
– supervisors	0.025	0.024	-0.144	0.098
	(0.086)	(0.032)	(0.371)	(0.281)
– clerical employees	0.051	-0.001	0.178	0.226
	(0.118)	(0.034)	(0.461)	(0.305)
– blue collar workers	0.018	0.024	0.130	0.601**
	(0.084)	(0.031)	(0.363)	(0.280)
Other firm characteristics:				
average incumbents' wage	0.028	-0.012	0.198**	0.287***
	(0.020)	(0.007)	(0.077)	(0.059)
log revenues	-0.008	0.016***	-0.012	-0.023
	(0.009)	(0.003)	(0.037)	(0.036)
log capital intensity	-0.023***	-0.006***	-0.080***	-0.060
	(0.008)	(0.002)	(0.030)	(0.037)
log materials	0.016*	0.002	0.070**	0.070***
	(0.010)	(0.002)	(0.028)	(0.020)
investment rate	0.000***	0.000**	0.002**	0.001**
	(0.000)	(0.000)	(0.001)	(0.001)
import dummy	-0.005	-0.031***	-0.141	-0.214***
	(0.040)	(0.007)	(0.091)	(0.055)
lag import dummy	0.088***	0.042***	0.462***	0.421***
	(0.020)	(0.007)	(0.066)	(0.050)
log imports	-0.008**	-0.001**	-0.031***	-0.022***
– (0 if none)	(0.003)	(0.001)	(0.010)	(0.007)
lag log imports	0.009***	0.004***	0.048***	0.045***
– (0 if none)	(0.002)	(0.001)	(0.006)	(0.005)
Observations	105,133	105,133	105,133	76,578
R-squared	0.458	0.268	0.602	0.604
F-test of IV exclusion	0,0145	0,1982	0,0008	0,0957

Sources: EAE-Trade-Postes 1995-2007. Specifications follow equations (6)-(8).The p-value of the joint exclusion of the instrument variables max(0,FDgr) and min(FDgr,0) is reported in the last row. The regressions include firm and year effects and are weighted by the number of new workers (Nin). Firm-level clustered standard errors are in parentheses; *** p<0.01, ** p<0.05, * p<0.1.