(Why) Are Internal Labor Markets Active in French Business Groups?*

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August 23, 2014

Abstract

Exploiting matched employer-employee data merged with information on the ownership structure of business groups, we document that French groups actively operate Internal Labor Markets (ILMs). On average, the probability that a firm hires a worker employed in its group exceeds by around 10 percentage points the probability to hire a worker employed outside the group. This excess probability is larger for job-to-job transitions involving managerial tasks and other high-skill occupations (engineers, high-level technicians, doctors and lawyers) as compared to transitions between unskilled occupations (blue collars, drivers and shop assistants). This suggests that ILMs add the most value with respect to the external labor market when informational asymmetries and training costs are large. We also find that the ILM is more active in groups that are more diversified, which supports the view that groups rely on the ILM to coordinate the employment response of affiliated firms to idiosyncratic shocks. In line with this, we also find that the ILM is particularly active in reallocating displaced workers when a firm or plant closure occurs within the group.

Keywords: Internal Labor Markets, Business Groups, Job-to-Job Mobility
JEL Classification: G30, L22, J08, J40

*We gratefully acknowledge financial support from the Axa Research Fund (Axa project "Internal Labor and Capital Markets in French Business Groups"). We thank INSEE (Institut National de la Statistique et des Études Économiques) and CASD (Centre d'accès securisé distant aux données) for providing access to the data and continuous technical support. We thank Andrea Alati and Edoardo Acabbi for excellent research assistance. We also thank participants at the 10th CSEF-IGIER Symposium on Economics and Institutions (Anacapri), the 2014 Barcelona GSE Forum and the Workshop on Global Challenges (Università di Milano). Chiara Fumagalli and Giovanni Pica acknowledge support from the Paolo Baffi Centre (Università Bocconi). Chiara Fumagalli also acknowledges support from IGIER. Giacinta Cestone acknowledges financial support from a Leverhulme Trust Research Project Grant and the City University London Pump Priming scheme.

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1 Introduction

Business groups are collections of legally independent firms that are partly or wholly owned by a single family or firm that controls the member firms' assets. They are a widespread organizational form in both developed and developing economies, and typically account for a large fraction of the economic activity in many of the countries where they are active.[1] An established view in the economics literature is that corporate groups fill an institutional void in countries and periods where external labor and financial markets display frictions (Khanna and Palepu (1997), Khanna and Yafeh (2007)). While a large body of work has analyzed groups' internal capital markets, little attention has been devoted to understand how groups use their internal labor markets (ILMs) to make up for dysfunctional external labor markets.[2] This paper contributes to fill this gap by investigating the functioning of internal labor markets in French business groups.[3]

There are several reasons why internal labor markets may have an advantage over external labor markets. First, redeploying workers across affiliated firms often involves lower dismissal penalties, both because of legal provisions that allow penalty-free transfers,[4] and because of internal coordination of labor adjustments which allows to avoid involuntary dismissal. Second, the internal labor market is likely to suffer less from informational asymmetries concerning workers' characteristics, and thus may have an advantage over the external market in matching a vacancy with the worker endowed with the specific skills required. Finally, the ILM may allow to better exploit costly training, and may spur workers to develop group-specific human capital. All these factors are likely to play a role in the French economy, where the costs of separations are high and the costs of hiring are non negligible for highly skilled workers (Abowd and Kramarz (2003)).

Our first aim is to document whether French groups actually operate internal labor markets,

[1]See La Porta, Lopez-de Silanes, and Shleifer (1999) and Faccio and Lang (2002).

[2]A large body of work has examined internal capital markets in conglomerates (see Stein (2003) and Maksimovic and Phillips (2013) for two good surveys), while several recent papers have focused on groups, showing that internal capital markets make affiliated firms more resilient. Gopalan, Nanda, and Seru (2007) find that intragroup loans within Indian business groups are used to support financially weaker firms so as to avoid default. Almeida and Kim (2013) find that reliance on internal capital markets allowed Korean groups to mitigate the effects of the 1998 Asian financial crisis on investment, while Boutin, Cestone, Fumagalli, Pica, and Serrano-Velarde (2013) show that access to internal capital markets is a source of competitive strength for group-affiliated firms when financial constraints bind. Our paper postulates that the possibility to adjust labor internally may be another factor explaining why group-affiliated firms are more resilient to shocks and display more competitive strength than stand-alone firms.

[3]France represents and interesting case study for investigating corporate groups. From 1999 to 2010, firms affiliated with groups accounted for around 40% of total employment, with substantial variability observed across sectors: in the financial sector affiliated firms account for more than 80% of total employment, whereas in agriculture the percentage is below 10%. Within manufacturing, on average affiliated firms account for almost 70% of total employment, but such share can be as high as 90% in automotive and energy.

[4]The EU Directive 96/71/EC facilitates unilateral transfers of employees among group-affiliated firms: intra-group transfers do not require each worker to be dismissed and rehired, and thus are not subject to employment protection regulations.

relying on a methodology that accounts for the endogeneity of group structure in terms of occupations. For instance, high intra-group mobility may well be observed because affiliated firms are intensive in occupations among which mobility is naturally high, and thus it is not *per se* evidence that ILMs function more smoothly than external labor markets. Indeed, our purpose is to isolate the contribution of the ILM channel to the probability that a worker transiting between two occupations is hired by a firm affiliated with the same group as the originating firm. We do so by controlling for firm $\times$ occupation of origin $\times$ occupation of destination fixed effects, thus comparing similar individuals – who make transitions between the same occupations and are hired by the same group affiliated firm – some coming from the group others coming from outside the group. This allows us to estimate our parameter of interest, i.e. the *excess probability* that a worker moving from two occupations is hired by a given firm if she was originally employed in the same group, over the probability to be hired by that firm if she was originally employed outside the group.

In order to implement this methodology, we need to rely upon a particularly rich data set: we not only need matched employer-employee data that allow us to identify job-to-job transitions but, for each affiliated firm, we also need information on the entire structure of the business group it belongs to, so as to separate job-to-job transitions originating from the group from those that do not originate from the group. To obtain this information we merge two data sets from the INSEE (Institut National de la Statistique et des Études Économiques). The first is the Déclarations Annuelles des Données Sociales (DADS), a matched employer-employee dataset with detailed individual-level and firm-level information. The second is the yearly survey run by the INSEE called LIFI (Enquête sur les Liaisons Financières entre sociétés). For each firm in the French economy, the LIFI allows us to assess whether the firm is group-affiliated or not and, for group firms, to identify the head of the group and all the other affiliated firms.

Based on these data, that span the period 2002-2010, we find that French business groups have indeed very active internal labor markets: for the average affiliated firm the probability to absorb a worker previously employed in the same group exceeds by around 10 percentage points the probability to absorb a worker not previously employed in the group. We also find that this excess probability is larger for job-to-job transitions involving managerial tasks and other human capital/information-intensive occupations (engineers, high-level technicians, doctors and lawyers), as compared to transitions between unskilled occupations (such as blue collars, drivers and shop assistants). This suggests that *informational* frictions and training costs play an important role in explaining groups' reliance on internal labor markets.[5]

[5]High-skill occupations are usually both information-intensive and human capital-intensive. In particular, it is difficult to assess a worker's skills, her fit with the corporate culture, or her suitability for a specific task without observing her performance for a certain period. This may explain why hiring on *external* labor markets is characterized

Motivated by these findings, we set to shed light on the conditions under which internal labor markets operate more intensely within groups. Our first finding is that the ILM is more active in groups that are more diversified, both in terms of sectors where affiliated firms operate and in terms of geographical location. This result suggests that groups rely on the ILM to coordinate the employment response of affiliated firms to idiosyncratic shocks. First, the internal labor market allows labor hoarding to take place at the group rather than the individual firm level: when one firm is hit by a negative shock, its healthy group affiliates can absorb the (skilled) labor force, thus allowing the group to save in firing costs and not to lose the accumulated human capital and the valuable information acquired on its skilled workers.[6,7] Secondly, the ILM may as well direct scarce human capital to group units that face profitable expansion opportunities and struggle to fill up job vacancies. Naturally, more diversified groups have more scope for reallocating human capital away from units hit by shocks and towards healthy and expanding units.[8]

To further explore how groups use the internal labor market in response to idiosyncratic shocks, we identify episodes of closure of affiliated firms/plants and we study how the ILMs respond to such closures. We find that the excess probability of hiring a worker originating from the group increases when some closure occurs in the rest of the group. Then, upon closure events, affiliated firms are even more prone to absorb workers from the ILM relative to normal times. We then focus our attention on the destination of displaced workers, i.e. workers displaced from their job as a consequence of a plant/firm closure. We find that a large proportion of the workers originating from an affiliated firm or plant that closes down are reemployed within the group. This confirms that closures activate the ILM, and also suggests that group ILMs play a role in providing workers with job stability in circumstances where large labor adjustments take place, thereby stimulating workers in investing in group-specific human capital.

By investigating the existence and the functions performed by internal labor markets in groups,

by search and training costs that are particularly high in the case of high-skilled workers (Abowd and Kramarz (2003), Blatter, Muehlemann, and Schenker (2012)), and suggests that internal labor markets allow to reduce search costs for high-skill occupations. Training costs may also be dampened when ILMs are operated, to the extent that for many high-skill occupations the training received within a job can be more easily redeployed in other tasks within the same organization.

[6] As documented in early work (Oi (1962), and Fay and Medoff (1985)), both firing and hiring (search and training) costs induce firms to hoard labor when hit by a negative shock; yet, labor hoarding is per se costly and not necessarily a feasible option for financially weak firms (see Sharpe (1994)).

[7] In Cestone, Fumagalli, Kramarz, and Pica (2014), we show that with ILMs bearing less frictions than the external labor market, even group firms that *do not* need to expand their labor force might use their financial slack to absorb workers from their liquidity-constrained group affiliates.

[8] A priori (sectoral and geographical) diversification exerts also a negative effect on the ILM activity: it is more difficult to redeploy workers across group units operating in different sectors because they may require sector-specific skills; similarly it is more difficult to move workers across units that are geographically dispersed because of trade unions resistance and employment protection regulation. Our results suggest that the positive effect of diversification prevails.

where labor is actively reallocated across affiliated firms, this paper builds a bridge across the labor/organizational economics literature and the finance literature. The labor literature has studied the functioning of internal labor markets *within firms*. Focusing on internal careers, a large body of work has shown how incentives to accumulate human capital and implicit insurance mechanisms can be provided through internal promotions.[9] Within the finance literature, many authors have claimed that internal labor markets in business groups operate alongside internal capital markets to make up for underdeveloped external markets (see Khanna and Palepu (1997); Khanna and Yafeh (2007)). However, little empirical work has investigated the functioning of ILMs in groups. In a small sample of large business groups in Chile and India, Khanna and Palepu (1999) find that intra-group mobility is high for managerial occupations. Belenzon and Tsomolon (2013) provide indirect evidence that in Western European countries ILMs allow groups to bypass employment protection regulation constraining the external labor market. Recent empirical studies of internal labor markets have focused on US-style conglomerates rather than groups. The paper closest to ours is Tate and Yang (2013): they find that US conglomerates respond to industry shocks resulting in a plant closure by redeploying workers internally, and that displaced workers who switch industries within the conglomerate do not face significant wage losses.[10]

The paper proceeds as follows. Section 2 illustrates our empirical approach. In Section 3 we describe the data and in Section 4 we discuss our results. Section 5 concludes.

2 The empirical model

If labor markets internal to groups suffer from the same amount of frictions as the external labor markets, we should observe that a group-affiliated firm with the same probability hires a worker from the internal and the external labor market. Instead, if internal labor markets are characterized by less severe frictions than external labor markets, groups should preferably rely on the ILM in order to adjust their labor force. In other words, group-affiliated firms should be more likely to absorb workers originating from their own group rather than from other firms in the economy; at the same time, workers who find a job in a group should be more likely - as compared to workers who find a job outside that group - to originate from an affiliated firm.

Our first aim is to verify which of the above hypothesis is confirmed by the data. However, in assessing whether internal labor markets facilitate within-group job-to-job mobility we face a major identification challenge, in that group structure (in terms of sectors, regions, occupations)

[9]See Gibbons and Waldman (1999), Lazear (1999), and Waldman (2012) for comprehensive surveys.

[10]While this points to the bright side of internal labor markets, Silva (2013) unveils their inefficiencies. He documents wage convergence within diversified firms, whereby conglomerate plants in low-wage sectors overpay workers as compared to stand-alone firms when the conglomerate is also present in high-wage industries.

is endogenous and may affect within-group mobility patterns. In fact, documenting that a large proportions of the workers hired by an affiliated firm were previously employed in the same group is not *per se* evidence that internal labor markets function more smoothly than external labor markets: intra-group mobility may be high because groups are composed of different firms that are intensive in occupations among which mobility is naturally high. Our aim is instead to isolate the contribution of the internal labor market channel to the probability that a worker transiting between two occupations is hired by a firm affiliated with the same group as the originating firm. To do that, we have to account for the counterfactual probability that the worker would have ended up in that firm even if she originally worked in a non-affiliated firm. In order to address this concern, we apply to our setting a methodology devised by Kramarz and Thesmar (2013) and Kramarz and Nordström Skans (2013) to measure the impact of networks on labor market outcomes.[11] We describe this methodology in the next Section.

2.1 Affiliated Firms Hiring Workers

Consider the triplet occupation of origin $o(i)$, occupation of destination $z(i)$, and firm j affiliated with a group. Denote as $c(i)$ the set of workers in occupation $o(i)$ at $t-1$ who move to occupation $z(i)$ in any firm at time t. We model the probability that worker i moving from occupation $o(i)$ to occupation $z(i)$ finds a job in the group-affiliated firm j in the following way:

$$E_{i,c(i),j} = \beta_{c(i),j} + \gamma_{c(i),j} BG_{i,j} + \varepsilon_{i,j} \tag{1}$$

where $E_{i,c(i),j}$ is an indicator variable taking the value one if worker i moving from occupation $o(i)$ to occupation $z(i)$ finds a job in firm j. $BG_{i,j}$ is an indicator variable that takes the value one if worker i's firm of origin belongs to the same group as the firm of destination j.

The term $\beta_{c(i),j}$ is a firm-occupation pair specific effect that captures the natural tendency of firm j to absorb workers transiting from occupation o to occupation z. This natural tendency measures the fact that occupation o may allow a worker to develop those skills that are particularly suitable to perform occupation z in firm j. Our parameter of interest is $\gamma_{c(i),j}$, that measures the *excess* probability of a worker moving from o to z to be absorbed by firm j if she comes from a firm affiliated with the same group as j, over the probability to be absorbed by firm j if the worker comes from a firm not affiliated with j's group. The error term $\varepsilon_{i,j}$ captures all other factors that affect the probability that worker i moving from occupation $o(i)$ to occupation $z(i)$ finds a job

[11] Kramarz and Thesmar (2013) assess whether the probability of being hired in a given firm is larger when the individual and the firm's CEO belong to the same network, while Kramarz and Nordström Skans (2013) find that graduates from a given class whose fathers are employed in a firm are more likely to be hired by that firm.

in firm j. We assume that $E(\varepsilon_{i,j}|BG_{i,j}, c(i) \times j) = 0$: conditional on observables, namely group affiliation and the absorbing firm-occupation of origin-occupation of destination fixed effect, the error has zero mean.

Direct estimation of equation (1) would require a data set with one observation for each combination of job mover, occupation of destination and firm of destination. As our data set contains 1,574,000 job-to-job transitions per year, 25 occupations and approximately 1,000,000 firms, the estimation of the model would require the construction of a data set with 40,000 billion observations. In order to estimate equation (1) while keeping the dimensionality of the problem reasonable, we take the approach that we describe next. We define:

$$R^{BG}_{c,j} \equiv \frac{\sum_{i \in c(i)} E_{i,c(i),j} BG_{i,j}}{\sum_{i \in c(i)} BG_{i,j}} = \beta_{c,j} + \gamma_{c,j} + \widetilde{u}^{BG}_{c,j} \tag{2}$$

as the fraction of workers that are hired by firm j among all workers moving from occupation o to z and that originate from a firm belonging to the same group as firm j. Note that this fraction might be high because firm j naturally tends to hire workers moving between occupations o and z and is part of a group that includes firms intensive in occupation o. In this case, one observes many transitions from occupation o to occupation z in firm j and originating from the group, but this cannot be ascribed to the internal labor market channel.

We then compute the fraction of workers that are hired by firm j among all workers moving from occupation o to z and whose firm of origin does not belong to the same group as firm j:

$$R^{-BG}_{c,j} \equiv \frac{\sum_{i \in c(i)} E_{i,c(i),j}(1 - BG_{i,j})}{\sum_{i \in c(i)}(1 - BG_{i,j})} = \beta_{c,j} + \widetilde{u}^{-BG}_{c,j} \tag{3}$$

Taking the difference between the two ratios eliminates the firm-class fixed effect $\beta_{c,j}$:

$$G_{cj} \equiv R^{BG}_{c,j} - R^{-BG}_{c,j} = \gamma_{c(i),j} + u^{G}_{i,j}. \tag{4}$$

The variable G is computed for each occupation pair-firm, and it is the difference between two probabilities: that of a given firm j absorbing workers (transiting between two occupations o and z) who are separating from an affiliated firm, and that of a given firm j absorbing workers (transiting between two occupations o and z) who are separating from a non-affiliated firm.

2.2 Workers Originating from Affiliated Firms

We now turn to a related albeit not identical question. Does reliance on internal labor markets make it more likely that a worker who finds a job in a group originates from an affiliated firm as compared to workers who find a job outside that group? To answer this question, we estimate the

excess probability that a worker (transiting between two occupations) originates from firm j if she lands to an affiliated firm, over the probability that the worker originates from firm j while landing to a non-affiliated firm.

As earlier, we denote as $c(i)$ the set of workers in occupation $o(i)$ at $t-1$ who move to occupation $z(i)$ in any firm at time t. We model the probability that worker i moving from occupation $o(i)$ to occupation $z(i)$ separates from firm j in the following way:

$$E^{O}_{i,c(i),j} = \beta^{O}_{c(i),j} + \gamma^{O}_{c(i),j} BG^{O}_{i,j} + \varepsilon^{O}_{i,j} \tag{5}$$

where $E^{O}_{i,c(i),j}$ is an indicator variable taking the value one if worker i moving from occupation $o(i)$ to occupation $z(i)$ separates from firm j. $BG^{O}_{i,j}$ is an indicator variable that takes the value one if worker i's firm of destination belongs to the same group as the firm of origin j.

The term $\beta^{O}_{c(i),j}$ is a firm-occupation pair specific effect that captures the natural tendency of workers moving from occupation $o(i)$ to occupation $z(i)$ to originate from firm j. This may be high due to the fact that carrying out occupation o in firm j endows a worker with the skills that facilitate moving to occupation z in any other firm. Our parameter of interest is $\gamma^{O}_{c(i),j}$, that measures the *excess* probability of a worker moving from o to z to originate from firm j if she lands to a firm affiliated with the same group as j, over the probability to originate from firm j if the worker lands to a firm not affiliated with j's group. The error term $\varepsilon^{O}_{i,j}$ captures all other factors that affect the probability that worker i moving from occupation $o(i)$ to occupation $z(i)$ originates from firm j.

We then define:

$$R^{BG,O}_{c,j} = \frac{\sum_{i \in c(i)} E^{O}_{i,c(i),j} BG^{O}_{i,j}}{\sum_{i \in c(i)} BG^{O}_{i,j}} = \beta^{O}_{c,j} + \gamma^{O}_{c,j} + \widetilde{u}^{BG,O}_{c,j} \tag{6}$$

as the fraction of workers that originate from firm j among all workers moving from occupation o to z whose firm of destination belongs to the same group as firm j. As discussed earlier, this fraction may be high because workers performing occupation o in firm j have a high propensity to move to occupation z in other firms, and the group includes firms intensive in occupation z. Hence, the observation of many transitions from occupation o in firm j to occupation z within the group cannot necessarily be ascribed to the ILM activity.

We then compute the fraction of workers that originate from firm j among all workers moving from occupation o to z and whose firm of destination does not belong to the same group as firm j:

$$R^{-BG,O}_{c,j} = \frac{\sum_{i \in c(i)} E^{O}_{i,c(i),j}(1 - BG^{O}_{i,j})}{\sum_{i \in c(i)}(1 - BG^{O}_{i,j})} = \beta^{O}_{c,j} + \widetilde{u}^{-BG,O}_{c,j} \tag{7}$$

Taking the difference between the two ratios eliminates the firm-occupation pair fixed effect $\beta^O_{c,j}$:

$$G^O_{cj} = R^{BG,O}_{c,j} - R^{-BG,O}_{c,j} = \gamma^O_{c,j} + u^{G,O}_{i,j} \tag{8}$$

The variable G is computed for each occupation pair-firm, and it is the difference between two probabilities: that of originating from firm j for workers (transiting between two occupations o and z) who land to an affiliated firm, and that of originating from firm j for workers (transiting between two occupations o and z) who land to a non-affiliated firm.

3 The data

The implementation of the methodology described in Sections 2.1 and 2.2 requires reliable information allowing us to follow employees from firm to firm and year to year. Moreover, for each firm, we need to identify the entire structure of the group that firm is affiliated with so as to distinguish transitions originating from (landing to) the firm's group and transitions that do not originate from (land to) the group. To obtain this information we have merged two data sets made available to us by the INSEE (Institut National de la Statistique et des Études Économiques).

Our main data source is the Déclarations Annuelles des Données Sociales (DADS), a large-scale administrative database of matched employer-employee information collected by INSEE. The data are based upon mandatory employer reports of the earnings of each employee subject to French payroll taxes. These taxes essentially apply to *all* employed persons in the economy (including self-employed). Each observation in DADS corresponds to a unique individual-plant combination in a given year, with detailed information about the plant-individual relationship. The data set includes the number of days during the calendar year that individual worked in that plant, the (gross and net) wage, the type of occupation (classified according to the socio-professional categories described in Table 1), the full time/part time status of the employee. Moreover, the data set provides the identifier of the firm that owns that plant, the geographical location of both the employing plant and firm, as well as the industry classification of the activity undertaken by the plant/firm. The special feature of DADS Postes, the version of DADS we have been given access to, is that it allows us to follow a worker along two consecutive years. More precisely, the DADS Postes referring to year t not only include detailed information regarding all the individual-plant relationships observed in year t, but for each individual they also provide detailed information concerning the plant relationships observed for that individual in year *t-1*. This structure allows us to identify workers transiting from

one firm to another along two consecutive years.[12,13]

The identification of group structure is based on the yearly survey run by the INSEE called LIFI (Enquête sur les Liaisons Financières entre sociétés). The LIFI contains information which makes it a unique data set for the study of business group activity. It collects information on direct financial links between firms, but it also accounts for indirect stakes and cross-ownerships. This is very important, as it allows INSEE to precisely identify the group structure even in the presence of pyramids. More precisely, LIFI defines a group as a set of firms controlled, directly or indirectly, by the same entity (the head of the group). The survey relies on a formal definition of *direct* control, requiring that a firm hold at least 50% of the voting rights in another firm's general assembly. This is in principle a very tight threshold, as in the presence of dispersed minority shareholders real control can be achieved with substantially lower equity stakes. However, we do not expect this to be a major source of bias in our sample, as most French firms are private and in France ownership concentration is strong even among listed firms.[14] Moreover, let us stress again that because both *indirect* control and cross-ownerships are accounted for in the LIFI, a group firm need not be directly controlled with a majority stake by the head of the group. For each firm in the French economy, the LIFI allows us to assess whether such firm is group-affiliated or not and, for affiliated firms, to identify the head of the group and all the other firms affiliated with the same group.

The merge of DADS Postes with LIFI allows us to distinguish between those transitions that originate from (lend to) the group a given firm is affiliated with and those transitions that do not. Moreover, we can build a number of variables on the characteristics of the group that firm is affiliated with, such as the total number of affiliated firms, total (full-time equivalent) employment and the geographical and sectoral diversification of the group activities.[15]

The merged data span the period 2002-2010. We remove from our samples the occupations of the Public Administration (33, 45 and 52 in Table 1) because the determinants of occupation in the public sector are likely to be different from those of the private sector. Moreover, as we focus on job-to-job transitions, we disregard transitions originating from (or flowing to) unemployment. We

[12]We cannot follow a given individual any longer because each yearly edition of DADS Postes randomly re-assignes individual identifiers.

[13]If an individual exhibits multiple firm relationships in a given year, we identify his/her main job by considering the relationship with the longest duration and for equal durations we consider the relationship with the highest qualification.

[14]In their overview of ownership structures and voting power in France, Bloch and Kremp (1999) show that ownership concentration is pervasive. For non listed companies with more that five hundreds employees, the main shareholder's stake is 88%. The degree of ownership concentration is slightly lower for listed companies, but still above 50% in most cases.

[15]These variables will be described more in detail below.

Table 1: Socio-professional categories

CODE	CATEGORY
10	Farmers
2	**Top manager/Chief of firms**
21	Top managers/chiefs of handicraft firms
22	Top managers/chiefs of industrial/commercial firms with less than 10 employees
23	Top managers of industrial/commercial firms with more than 10 employees
3	**Management and superior intellectual occupations**
31	Healthcare professionals, legal professionals and other professionals
33	Managers of the Public Administration
34	Professors, researchers, scientific occupations
35	Journalists, media, arts and entertainment occupations
37	Administrative and commercial managers
38	Engineers and technical managers
4	**Intermediate occupations**
42	Teachers and other education, training and library occupations
43	Healthcare support occupations and social services occupations
44	Clergy and religious occupations
45	Intermediate administrative occupations in the Public Administration
46	Intermediate administrative and commercial occupations in firms
47	Technicians
48	Supervisors and 'agents de maitrise'
5	**White collar occupations**
52	White collar occupations in the Public Administration
53	Surveillance and security occupations
54	Administrative white collars in firms
55	Sales and related occupations
56	Personal service occupations
6	**Blue collar occupations**
62	Industrial qualified workers
63	Handicraft qualified workers
64	Drivers
65	Maintenance, repair and transport qualified workers
67	Industrial non qualified workers
68	Handicraft non qualified workers
69	Agricultural worker

Source: INSEE.

also remove temporary agencies and observations with missing wages. Finally, we also remove from the data set those employers classified as 'particulier employeur': they are individuals employing workers that provide services in support of the family, such as cleaners, nannies and caregivers for elderly people.[16,17]

These restrictions leave us with, on average, 1,574,000 job-to-job transitions per year during the sample period.

3.1 Identification of the set of workers transiting between occupations

Our data sources allow us to identify those workers that change job from one year to the other, with detailed information regarding the occupation of origin and of destination. Based on this, for each occupation pair $o - z$, we identify the set of workers $c(i)$ moving from occupation o to occupation z between year $t-1$ and year t. Then, we associate each occupation pair $o - z$ with a firm j. This means that, for each firm j, we have as many triplets $o - z - j$ as the total number of occupation pairs, i.e. 625. For each triplet $o - z - j$, we separate those transitions that originate from (land to) the same group as firm j from those transitions that do not. This allows us to compute the denominators of the ratios $R^{BG}_{c,j}$ and $R^{-BG}_{c,j}$ indicated in (2) and (3) for inflows. (Similarly for outflows). We then drop the triplets in which this distinction cannot be drawn because either all the transitions originate from (land to) j's group or all the transitions originate from (land to) the external labor market. Trivially, on those sets of workers it is not possible to estimate the excess probabilities. This restriction is without loss of identifying variation since the discarded observations are uninformative conditional on the fixed effects.

This leaves us with approximately one million occupation pair-firm triplets per year. For each triplet $o-z-j$, we then compute the number of workers transiting from occupation o to occupation z that are hired by firm j, distinguishing between those that originate from the same group as firm j and those that do not. This allows us to compute the numerator of the ratios $R^{BG}_{c,j}$ and $R^{-BG}_{c,j}$ indicated in (2) and (3) for inflows, and ultimately to estimate our parameter of interest $\gamma_{c,j}$ for each triplet. A similar procedure applies to outflows. The next Section illustrates the results our estimation procedure.

[16]From 2008 the mandatory report has been extended also to these employers.

[17]We remove also those employers classified as 'fictitious' because the code identifying either the firm or the plant communicated by the employer to the French authority does not belong to the existing ones and is, therefore, incorrect.

4 Results

4.1 Internal labor markets at work

We aggregate the parameters estimated for the triplets $o-z-j$ at the firm level. First, we take the simple average of all the $\gamma_{c,j}$ ($\gamma^{O}_{c,j}$) computed for firm j. Second, we take the weighted average of those parameters. The weight assigned to the parameter gamma referred to the triplet $o-z-j$ is the importance of the transitions from occupation o to occupation z for the group firm j is affiliated with. In other words, the weight is the ratio of the number of transitions from occupation o to occupation z that originate from (land to) firm j's group to the total number of transitions (for all the occupation pairs associated with firm j) that originate from (land to) firm j's group.

Table 2 and 3 show the firm-level average excess probability, referred to inflows and outflows respectively. The year appearing in the first column indicates the year in which workers transiting from one job to the other were hired (for inflows) and dismissed (for outflows). The upper panel of the Tables shows simple averages. Focusing on inflows (Table 2), we find that for the average firm the probability to absorb a worker previously employed in the same group exceeds by 10 percentage points the probability to absorb a worker not previously employed in the group. Table 3 complements Table 2 by considering outflows. We obtain very similar figures: the probability that a worker separates from a firm if she is moving to an affiliated firm exceeds by 10 percentage points the probability that the worker separates from that firm if she is moving to a non-affiliated firm. The bottom panel of the tables shows weighted averaged. The results are pretty similar to unweighted averages.

In the analysis above, we have defined as $c(i)$ the set of workers moving between a given occupation pair in the whole French economy. This set has been then divided in the two subsets described above, depending on whether the transitions originate from (lend to) the same group as firm j or not. One may raise the concern that such subsets are not homogeneous. Imagine, for instance, that a group has units that are all located within the same department.[18] It follows that all the transitions origination from that group will also originate from that particular department, whereas the transitions originating outside the group may come from any department in France. The pool of workers firm j will draw upon are then not fully comparable. To address this concern, we introduce a restriction in the definition of the set $c(i)$. Namely, we define as $c(i)$ the set of all the transitions occurring between occupation o and occupation z that originate from (land to) the same departments in which firms affiliated with j's group are active. Within this set, the

[18] In the administrative division of France, *departments* represent one of the three levels of goverment below the national level, between the region and the commune. There are 96 departments in mentropolitan France and 5 overseas departments.

Table 2: Inflows - CS Classification

Year	Mean	St.Err.	Percentiles 50	75	95	N
	Unweighted firm-level aggregation					
2003	0.10002	0.00144	0	0.02083	0.83333	28817
2004	0.10439	0.00150	0	0.02427	0.92892	27881
2005	0.10597	0.00147	0	0.02603	0.95525	29369
2006	0.10598	0.00143	0	0.02654	0.98197	31152
2007	0.09789	0.00134	0	0.01667	0.81715	32949
2008	0.08788	0.00112	0	0.00640	0.66667	42529
2009	0.09952	0.00129	0	0.01233	0.90519	36531
2010	0.09712	0.00123	0	0.00873	0.94375	37833
	Weighted firm-level aggregation					
2003	0.09395	0.00142	0	0.01886	0.83333	28817
2004	0.09832	0.00148	0	0.02083	0.92857	27881
2005	0.09922	0.00145	0	0.02189	0.94667	29369
2006	0.09918	0.00141	0	0.02270	0.97303	31152
2007	0.09147	0.00131	0	0.01576	0.80000	32949
2008	0.08160	0.00110	0	0.00662	0.66667	42529
2009	0.09341	0.00127	0	0.01286	0.89998	36531
2010	0.09139	0.00125	0	0.00935	0.92291	37833

Table 3: Outflows - CS Classification

Year	Mean	St.Err.	Percentiles 50	75	95	N
	Unweighted firm-level aggregation					
2002	0.10078	0.00146	0	0.02376	0.83333	28269
2003	0.10713	0.00154	0	0.03125	0.93779	26900
2004	0.11095	0.00154	0	0.03426	0.99995	27926
2005	0.10824	0.00146	0	0.03124	0.99983	30415
2006	0.10223	0.00140	0	0.02538	0.85467	31520
2007	0.08997	0.00115	0	0.00980	0.69995	41124
2008	0.09888	0.00129	0	0.01333	0.88888	36557
2009	0.10157	0.00133	0	0.01514	0.97259	35593
	Weighted firm-level aggregation					
2002	0.09374	0.00143	0	0.01922	0.83333	28269
2003	0.10013	0.00151	0	0.02553	0.93330	26900
2004	0.10308	0.00151	0	0.02808	0.99996	27926
2005	0.10072	0.00143	0	0.02531	0.99983	30415
2006	0.09473	0.00136	0	0.02214	0.83525	31520
2007	0.08290	0.00112	0	0.00950	0.66667	41124
2008	0.09254	0.00123	0	0.01315	0.88888	36557
2009	0.09463	0.00130	0	0.01435	0.96552	35593

subset of transitions originating from (landing to) the group of firm j will be the same as before. Instead, the subset of transitions occurring outside the group will be smaller, thereby decreasing the denominator of the ratio $R_{c,j}^{-BG}$ (for inflows) and $R_{c,j}^{-BG,O}$ (for outflows). Also the numerator of those ratios - the number of workers hired (dismissed) by firm j that do not originate from (land to) the group - is likely to decrease, once we restrict the set of eligible workers. However, the former effect comes out to be stronger, and the department restriction in the definition of the set $c(i)$ leads to an increase in the correction term $\beta_{c,j}$ ($\beta_{c,j}^{O}$) and to a decrease in the excess probability $\gamma_{c,j}$ ($\gamma_{c,j}^{O}$) computed for the triplets $o - z - j$. This translates into a (minor) decrease in the value of the firm-level average excess probability, as Tables 4 and 5 show.[19]

As a robustness check we estimate our parameter of interest using a different classification of occupations and therefore of the set of transiting workers $c(i)$. We group the categories indicated in Table 1 in seven broader categories: non-qualified blue collars (including 67,68,69), qualified blu collars (62, 63, 64, 65), non-qualified white collars (53), qualified white collars (54, 55, 56), intermediate professions (42, 43, 46, 47, 48), managers (21, 22, 23, 31, 34, 35, 37 38) and farmers (10). These categories are broader and may include occupations that are highly substitutable and between which job-to-job transitions are very likely to occur and other occupations between which transitions are much less likely. Therefore, for each pair of aggregated categories, we compute the frequencies of the transitions occurring between each pair of the corresponding sub-categories (according to Table 1). We then split these pairs in the group having above-median frequencies and the one having below-median frequencies. For instance, consider the pair Qualified Blue Collars - Qualified White Collars. We compute the frequencies of the transitions occurring between the twelve corresponding sub-categories (62-54, 62-55, 62-56 etc.) and then we split these pairs in the group QBC-QWC-high frequency and the group QBC-QWC-low frequency. For the pair of aggregated categories characterised by the same occupation of origin and destination (say Qualified Blue Collars - Qualified Blue Collars) we create an additional group including all the disaggregated pairs having the same occupation of origin and of destination (say 62-62, 63-63, etc.). In sum, we split each one of the forty-nine aggregated occupation pairs in two or three new occupation pairs and we compute our parameter of interest $\gamma_{c,j}$ ($\gamma_{c,j}^{O}$) based on them. We then aggregate at the firm-level, both computing simple average and weighted averages. As shown in Table 18 and 19, reported in Appendix A.1, the estimated excess probabilities are slightly lower but the order of

[19]We also introduce a restriction based on the regions in which affiliated firms are active. The correction term increases, but it increases less as compared to the case in which the department restriction is imposed. Consequently, the estimated excess probability decreases, but it decreases less relative to the case in which the department restriction is imposed, with the firm-level average excess probability falling in-between the values found without imposing restrictions and the values found imposing the department restriction. The corresponding tables are available upon request.

Table 4: Inflows - CS Classification (Department Restriction)

			Percentiles			
Year	Mean	St.Err.	50	75	95	N
	Unweighted firm-level aggregation					
2003	0.09794	0.00143	0	0.01923	0.80915	28775
2004	0.10266	0.00150	0	0.02270	0.91667	27841
2005	0.10384	0.00147	0	0.02414	0.93594	29307
2006	0.10384	0.00143	0	0.02480	0.94444	31105
2007	0.09598	0.00133	0	0.01556	0.80000	32904
2008	0.08659	0.00112	0	0.00595	0.66667	42500
2009	0.09768	0.00129	0	0.01118	0.87500	36480
2010	0.09563	0.00127	0	0.00800	0.92299	37791
	Weighted firm-level aggregation					
2003	0.09199	0.00141	0	0.01780	0.80708	28775
2004	0.09671	0.00148	0	0.02000	0.91300	27841
2005	0.09728	0.00144	0	0.02041	0.92000	29307
2006	0.09714	0.00140	0	0.02113	0.94118	31105
2007	0.08968	0.00131	0	0.01484	0.79963	32904
2008	0.08038	0.001110	0	0.00621	0.66667	42500
2009	0.09167	0.00127	0	0.01205	0.88092	36480
2010	0.08996	0.00125	0	0.00877	0.90687	37791

Table 5: Outflows - CS Classification (Department Restriction)

			Percentiles			
Year	Mean	St.Err.	50	75	95	N
	Unweighted firm-level aggregation					
2002	0.09866	0.00145	0	0.02191	0.82071	28205
2003	0.10524	0.00154	0	0.02939	0.91964	26862
2004	0.10871	0.00153	0	0.03246	0.99355	27880
2005	0.10585	0.00145	0	0.02857	0.97727	30364
2006	0.10025	0.00138	0	0.02419	0.83333	31478
2007	0.08868	0.00115	0	0.00926	0.68571	41101
2008	0.09724	0.00129	0	0.01249	0.87482	36516
2009	0.10003	0.00133	0	0.01429	0.95833	35555
	Weighted firm-level aggregation					
2002	0.09174	0.00142	0	0.01846	0.80401	28205
2003	0.09839	0.00151	0	0.02381	0.91985	26862
2004	0.10104	0.00150	0	0.02632	0.99271	27880
2005	0.09849	0.00143	0	0.02381	0.96295	30364
2006	0.09289	0.00135	0	0.02102	0.81818	31478
2007	0.08173	0.00112	0	0.00901	0.66667	41101
2008	0.09102	0.00126	0	0.01258	0.87500	36516
2009	0.09318	0.00130	0	0.01408	0.94905	35555

magnitude does not change. (We obtain similar results for outflows.)

Overall, our evidence strongly suggests that ILMs operating within French corporate groups exhibit less frictions than external labor markets: job transitions between different occupations are facilitated when taking place within the same group. This motivates us to investigate the determinants of the ILM effect on workers' mobility.

4.2 For which occupations is the ILM more active?

In this section we explore whether some occupation pairs exhibit a larger internal labor market activity than others. We refer to the disaggregated parameters $\gamma_{c,j}$ ($\gamma^{O}_{c,j}$) estimated for the triplets $o - z - j$, and then we compute the average excess probability over all the triplets having the same occupation of origin (left side of Tables 6 and 8 for inflows and outflows, respectively), the same occupation of destination (right side of Tables 6 and 8), and over all the triplets having the same occupation pair (Tables 7 and 9).[20] The results displayed by the tables are net of the firm and year fixed effects, so as to account for any firm specificity that may affect the ILM activity concerning particular occupations. For instance, it might be the case that transitions between two specific occupations occur especially in larger firms (or in firms belonging to larger/more diversified groups) in which the ILM activity might be more intense.

A clear pattern emerges: the ILM effect is strong for job-to-job transitions involving managerial occupations and other high-skill occupations (such as engineers, high-level technicians, doctors and lawyers), whereas it is weak for unskilled occupations (such as blue collars, drivers and shop assistants). This suggests that internal labor markets play an important role when *informational* frictions and training costs are particularly severe. Indeed, evidence of high search and training costs (see the Introduction for evidence on this) for skilled workers supports the notion that high-skill occupations are both information-intensive and human capital-intensive. This in turn suggests that identifying and hiring high-skill workers within an internal labor markets may allow groups to substantially reduce labor adjustment costs.

4.3 Which groups have a more active ILM?

An interesting feature emerges from tables 2 to 5: the ILM parameter γ_j is positive only for firms belonging to the top quartile of the distribution and is zero for many firms in our sample. This suggests that the ILM channel is active for firms with specific characteristics, possibly affiliated with groups with specific characteristics. This consideration is reinforced by the observation that

[20]The tables focus on the $\gamma_{c,j}$ estimated using the CS classification of the occupations and imposing the department restriction. We obtain very similar results with all the alternative specifications.

Table 6: Inflows - Rankings by occupation of origin/occupation of destination net of year and firm fixed effect (Department restriction)

Occupation of origin	Code	Mean	**Occupation of destination**	Code	Mean
Top managers of industrial/commercial firms with more than 10 employees	23	0.03623	Top managers of industrial/commercial firms with more than 10 employees	23	0.04009
Top managers of industrial/commercial firms with less than 10 employees	22	0.03183	Top managers of industrial/commercial firms with less than 10 employees	22	0.03539
Administrative and commercial managers	37	0.02567	Top managers/chiefs of handicraft firms	21	0.03080
Healthcare professionals, legal professionals and other professionals	31	0.02502	Administrative and commercial managers	37	0.02497
Engineers and technical managers	38	0.02485	Supervisors and 'agents de maitrise'	48	0.02463
Supervisors and 'agents de maitrise'	48	0.02287	Healthcare professionals, legal professionals and other professionals	31	0.02271
Top managers/chiefs of handicraft firms	21	0.02110	Engineers and technical managers	38	0.02223
Maintenance, repair and transport qualified workers	65	0.02173	Professors, researchers, scientific occupations	34	0.02179
Professors, researchers, scientific occupations	34	0.02134	Maintenance, repair and transport qualified workers	65	0.02142
Technicians	47	0.02106	Agricultural worker	69	0.02004
Teachers and other education, training and library occupations	42	0.01991	Technicians	47	0.01996
Intermediate administrative and commercial occupations in firms	46	0.01980	Intermediate administrative and commercial occupations in firms	46	0.01906
Agricultural worker	69	0.01979	Surveillance and security occupations	53	0.01857
Surveillance and security occupations	53	0.01836	Teachers and other education, training and library occupations	42	0.01823
Handicraft qualified workers	63	0.01735	Journalists, media, arts and entertainment occupations	35	0.01758
Administrative white collars in firms	54	0.01726	Industrial qualified workers	62	0.01753
Healthcare support occupations and social services occupations	43	0.01723	Administrative white collars in firms	54	0.01713
Industrial qualified workers	62	0.01716	Industrial non qualified workers	67	0.01679
Journalists, media, arts and entertainment occupations	35	0.01682	Healthcare support occupations and social services occupations	43	0.01679
Handicraft non qualified workers	68	0.01680	Handicraft non qualified workers	68	0.01652
Drivers	64	0.01603	Handicraft qualified workers	63	0.01644
Industrial non qualified workers	67	0.01494	Sales and related occupations	55	0.01544
Sales and related occupations	55	0.01479	Drivers	64	0.01466
Personal service occupations	56	0.01077	Personal service occupations	56	0.01448

Table 7: Inflows - Rankings by occupation pairs net of year and firm fixed effect: top ten, bottom ten (Department restriction)

TOP TEN

Occupation pair	Code	Mean
Professors, researchers, scientific occupations-Top managers of industrial/commercial firms with more than 10 employees	34-23	0.05179
Top managers of industrial/commercial firms with more than 10 employees -Professors, researchers, scientific occupations	23-34	0.04803
Top managers of industrial/commercial firms with more than 10 employees-Top managers of industrial/commercial firms with more than 10 employees	23-23	0.04408
Top managers/chiefs of industrial/commercial firms with less than 10 employees-Top managers of industrial/commercial firms with more than 10 employees	22-23	0.03798
Top managers of industrial/commercial firms with more than 10 employees-Administrative and commercial managers	23-37	0.03481
Top managers of industrial/commercial firms with more than 10 employees-Administrative and commercial managers	37-23	0.03410
Top managers/chiefs of industrial/commercial firms with less than 10 employees- Administrative and commercial managers	22-37	0.03320
Administrative and commercial managers-Top managers/chiefs of industrial/commercial firms with less than 10 employees	37-22	0.03201
Supervisors and 'agents de maitrise'-Supervisors and 'agents de maitrise'	48-48	0.03187

BOTTOM TEN

Occupation pair	Code	Mean
Personal service occupations-Administrative white collars in firms	56-54	0.0118
Handicraft non qualified workers- Handicraft qualified workers	68-63	0.01349
Industrial qualified workers-Industrial non qualified workers	62-67	0.01345
Sales and related occupations-Administrative white collars in firms	55-54	0.01231
Industrial non qualified workers-Industrial qualified workers	67-62	0.01203
Industrial qualified workers - Industrial qualified workers	62-62	0.01010
Handicraft qualified workers-Handicraft qualified workers	63-63	0.00984
Sales and related occupations-Sales and related occupations	55-55	0.00778
Personal service occupations-Personal service occupations	56-56	0.00608
Drivers-Drivers	64-64	0.00341

Table 8: Outflows - Rankings by occupation of origin/occupation of destination (Department correction and fixed effects)

Occupation of origin	Code	Mean	**Occupation of destination**	Code	Mean
Top managers of industrial/commercial firms with more than 10 employees	23	0.0370	Top managers/chiefs of industrial/commercial firms with less than 10 employees	22	0.0351
Top managers/chiefs of industrial/commercial firms with less than 10 employees	22	0.0268	Top managers of industrial/commercial firms with more than 10 employees	23	0.0350
Administrative and commercial managers	37	0.0248	Top managers/chiefs of handicraft firms	21	0.0320
Supervisors and 'agents de maitrise'	48	0.0230	Administrative and commercial managers	37	0.0237
Healthcare professionals, legal professionals and other professionals	31	0.0223	Healthcare professionals, legal professionals and other professionals	31	0.0228
Engineers and technical managers	38	0.0213	Supervisors and 'agents de maitrise'	48	0.0223
Top managers/chiefs of handicraft firms	21	0.0195	Professors, researchers, scientific occupations	34	0.0200
Intermediate administrative and commercial occupations in firms	46	0.0181	Engineers and technical managers	38	0.0199
Technicians	47	0.0179	Intermediate administrative and commercial occupations in firms	46	0.0176
Professors, researchers, scientific occupations	34	0.0177	Teachers and other education, training and library occupations	42	0.0176
Maintenance, repair and transport qualified workers	65	0.0172	Agricultural worker	69	0.0175
Surveillance and security occupations	53	0.0168	Technicians	47	0.0173
Teachers and other education, training and library occupations	42	0.0161	Maintenance, repair and transport qualified workers	65	0.0171
Agricultural worker	69	0.0151	Surveillance and security occupations	53	0.0161
Administrative white collars in firms	54	0.0151	Journalists, media, arts and entertainment occupations	35	0.0155
Journalists, media, arts and entertainment occupations	35	0.0150	Healthcare support occupations and social services occupations	43	0.0152
Industrial qualified workers	62	0.0145	Administrative white collars in firms	54	0.0151
Handicraft qualified workers	63	0.0144	Handicraft non qualified workers	68	0.0144
Healthcare support occupations and social services occupations	43	0.0144	Handicraft qualified workers	63	0.0143
Handicraft non qualified workers	68	0.0143	Drivers	64	0.0132
Drivers	64	0.0139	Sales and related occupations	55	0.0129
Sales and related occupations	55	0.0130	Industrial qualified workers	62	0.0128
Personal service occupations	56	0.0128	Personal service occupations	56	0.0122
Industrial non qualified workers	67	0.0101	Industrial non qualified workers	67	0.0107

Table 9: Outflows - Rankings by occupation pairs: top ten, bottom ten (Department correction and fixed effects)

TOP TEN

Occupation pair	Code	Mean
Top managers of industrial/commercial firms with more than 10 employees-Professors, researchers, scientific occupations	23-34	0.0591
Top managers of industrial/commercial firms with more than 10 employees-Top managers of industrial/commercial firms with more than 10 employees	23-23	0.0455
Top managers of industrial/commercial firms with more than 10 employees-Top managers/chiefs of industrial/commercial firms with less than 10 employees	23-22	0.0375
Administrative and commercial managers-Top managers/chiefs of industrial/commercial firms with less than 10 employees	37-22	0.0357
Top managers of industrial/commercial firms with more than 10 employees-Administrative and commercial managers	23-37	0.0356
Professors, researchers, scientific occupations Top managers of industrial/commercial firms with more than 10 employees	34-23	0.0344
Top managers of industrial/commercial firms with more than 10 employees-Administrative white collars in firms	23-54	0.0347
Administrative and commercial managers-Top managers of industrial/commercial firms with more than 10 employees	37-23	0.0332
Top managers of industrial/commercial firms with more than 10 employees-Journalists, media, arts and entertainment occupations	23-35	0.0321
Top managers of industrial/commercial firms with more than 10 employees-Engineers and technical managers	23-38	0.0312

BOTTOM TEN

Occupation pair	Code	Mean
Industrial non qualified workers -Handicraft non qualified workers	67-68	0.0102
Industrial non qualified workers - Administrative white collars in firms	67-54	0.0100
Handicraft qualified workers-Handicraft qualified workers	63-63	0.0077
Industrial qualified workers -Industrial non qualified workers	62-67	0.0065
Sales and related occupations-Sales and related occupations	55-55	0.0055
Industrial qualified workers -Industrial qualified workers	62-62	0.0050
Personal service occupations -Personal service occupations	56-56	0.0037
Industrial non qualified workers-Industrial qualified workers	67-62	0.0032
Drivers-Drivers	64-64	0.0027
Industrial non qualified workers-Industrial non qualified workers	67-67	-0.0005

the population of French groups is highly heterogeneous: there exist few large groups, with many large affiliates that are diversified both from a sectoral and geographical perspective; and many small groups, with few small affiliates that are hardly diversified. Looking at the distribution of group size in France, measured by group total employment, one finds out that groups belonging to the top decile on average have 20 affiliates, employ 800 workers per unit, operate in 7 different four-digit industries and in 4 different regions. Instead, groups in the rest of the population have less than 5 units, employ less than 50 workers per-unit, operate in less than 3 different four-digit sectors and mostly in the same region.

These facts motivate us to investigate which firm and group characteristics are associated with a larger ILM parameter (γ_j), focusing in particular on the role of group diversification. A priori diversification may exert two opposite effects on ILM activity. On the one hand, firms in more diversified groups are likely to be hit by idiosyncratic shocks, which creates more scope for ILM reallocations. On the other hand, units operating in different sectors may demand sector-specific skills, which should hinder intra-group mobility within diversified groups. In fact, as shown in Section 4.2, large part of the ILM activity in French groups pertains to occupations characterized by broader skills, easily redeployable across different sectors.

To this purpose, we estimate the following model:

$$\gamma_{j,g(j),t} = \delta Div_{g(j),t} + \zeta gsize_{g(j),t} + \theta Div_{g(j),t} \times gsize_{g(j),t} + \beta X_{j,g(j),t} + a_{j,g(j)} + b_t + \varepsilon_{j,g(j),t} \quad (9)$$

where $Div_{g(j),t}$ is a time-varying measure of (sectoral and geographical) diversification of the group g firm j is affiliated with; $gsize_{g(j),t}$ is the number of employees of (the rest of) the group at time t; the matrix $X_{j,g(j),t}$ includes additional firm- and group-level controls. The descriptive statistics of our control variables are shown in Table 10.[21] Finally, the model includes firm×group fixed effects to account for unobserved heterogeneity at the firm×group-level and year dummies to control for macroeconomic shocks common to all firms. The parameter θ, in this context, measures the differential impact of diversification for groups of different size on the amount of ILM activity.

Tables 11 and 12 show the results obtained when we focus on inflows, i.e. on the excess probability of hiring a worker originating the same group over the probability of hiring a worker who is not already employed in the group. In fact these tables suggest that, of the opposite effects of diversification mentioned above, the former prevails: diversification is associated with a more intense ILM activity within groups. Table 11 focuses on sectoral diversification. We compute an inverse measure of group diversification by measuring the share of the group total employment that

[21] Note that descriptive statistics are computed at the *firm level*. Hence, large groups are over-represented and the average group characteristics turn out to be larger as compared to the ones computed at the group level and mentioned at the beginning of this Section.

is accounted for by units active in each macrosector/4-digit sector; then we take the sum of the squared values of these shares.[22] We interpret the results in the light of the trade-off discussed above: when affiliated firms operate in very distant sectors, skill specialization limits the scope for intra-group mobility; in fact, as columns 2 and 3 show, when we compute diversification across macrosectors (agriculture, service, finance, manifacturing, automotive and energy), we do not find any significant effect on ILM activity. Instead, when firms are diversified within macrosectors, then exposure to idiosyncratic shocks tends to prevail: as column 4 shows, a firm has a more pronounced tendency to hire from the ILM (relative to the external labor market) when it is affiliated with a group that is more diversified across 4-digit sectors. Moreover, column 5 indicates that the effect of diversification is stronger in larger groups, where the internal labor market is thicker. A very similar pattern emerges when we measure group diversification by counting the number of 4-digit sectors in which affiliated firms are active.[23]

Table 12 focuses instead on geographical diversification. We first compute the share of total employment of the group that is accounted for by units located within the Paris area and outside the Paris area, respectively. Our inverse measure of diversification is the sum of the squared values of these shares. Then we perform the same exercise by computing employment shares referred to regions, i.e. the share of total employment of the group accounted for by units located in each region in France. As shown by columns 1 and 3, firms rely more on the ILM when they are affiliated with a group that is more dispersed from the geographical perspective. Moreover, this effect is stronger in larger groups (columns 2 and 4). A priori, also geographical diversification exerts two opposite effects on the ILM activity. Geographical dispersion should favor ILM activity by making it more likely that shocks hitting affiliated firms are unrelated. However, moving workers across more distant geographical areas might be more difficult, for instance because of trade unions resistance and employment protection regulation. Our results suggest that the former effect prevails. We also find that the ILM activity seems to be independent of whether the head of the group is state owned; instead, ILM activity is less intense when the head of the group is foreign.[24]

[22]Essentially, we compute an Herfindahl-Hirshman Index based on the employment shares of the group in the different macrosectors/4-digit sectors.

[23]The HHI-based measure of diversification weights group participation in a given sector with the importance of the group activity in that sector.

[24]Note that the negative correlation between the number of affiliated firms and the excess probability displayed in the Tables is driven by a mechanical effect. Firms affiliated with larger groups are likely to have a higher number of triplets $o-z-j$ associated with them. Remember that, in order to compute our parameter of interest $\gamma_{c,j}$ we disregard all the triplets in which *all* the transitions from occupation o to occupation z originate from outside the group firm j is affiliated with. Now, groups composed by larger units or by a higher number of units have a more heterogeneous workforce, hence we observe transitions originating from firm j's group for a higher number of occupation pairs. This implies that we disregard fewer triplets when firm j is affiliated with a larger group. *Ceteris paribus*, the higher number of triplets over which it is possible to compute our parameter of interest $\gamma_{c,j}$ disproportionately generates a higher number of $\gamma_{c,j} = 0$, which decreases the average γ of firm j.

Table 10: **Descriptive Statistics (Firm-level)**

	Mean	**St.dev.**	**Min**	**Max**	**N**
$\overline{\gamma}_{jt}$	0.098	0.24	-0.64	1	232,646
Firm size (empl.)	168.61	1573.82	0.005	217640	232,646
Rest of the group size (empl.)	10327	20578,28	0.001	349038	232,646
Number of 4 digit sectors	11	17.39	1	92	232,646
Number of macrosectors	1.88	0.99	1	6	232,646
Number of regions	5.32	6.24	1	22	232,646
HHI (macro sectors)	0.87	0.18	0.26	1	232,646
HHI (4-digit sectors)	0.58	0.27	0.08	1	232,646
HHI (Paris)	0.85	0.19	0.5	1	232,646
HHI (Regions)	0.71	0.30	0.08	1	232,646
% of firms that close	0.015	0.12	0	1	232,646
Number of firm closure in the rest of the group	1.55	4.99	0	68	232,646
% of firms for which at least one firm closes	0.28	0.45	0	1	232,646
in the rest of the group					232,646
Number of plant closure in the group	15.71	98.69	0	2149	232,646
% of firms for which at least one plant closes	0.45	0.50	0	1	232,646
in the group					

Note: *HHI (macrosectors)* is computed as the sum of the squares of the employment shares of all firms affiliated with a group, where each share is the ratio of the total employment of affiliated firms active in a given macrosectors over the total employment of the group. Macrosectors are agriculture, service, finance, manifacturing, energy, automotive. *HHI (4-digit)* is computed as the sum of the squares of the employment shares of all firms affiliated with a group, where each share is the ratio of the total employment of affiliated firms active in a given 4-digit sector to the total employment of the group. *HHI (Paris Area)* is computed as the sum of the squares of the employment shares of all firms affiliated with a group, where each share is the ratio of the total employment of affiliated firms active in the Paris Area/outside the Paris Area over the total employment of the group. *HHI (Region)* is computed as the sum of the squares of the employment shares of all firms affiliated with a group, where each share is the ratio of the total employment of affiliated firms active in a given region over the total employment of the group. We denote as *firm/plant closure* a situation in which a firm/plant sees its employment drop by more than 90% from one year to the other. Moreover, in order to avoid denoting as a closure a situation in which a firm/plant simply changes identifier, we remove all the cases in which more than 70% of the lost employment ends up in the same firm/plant.

Tables 13 and 14 show that similar qualitative results are obtained when we focus on outflows, i.e. on the excess probability of a worker that find a job in a group to originate from an affiliated firm over the probability of a worker who fidns a job outside the group.

4.4 Results: the Internal Labor Market and firm/plant closures

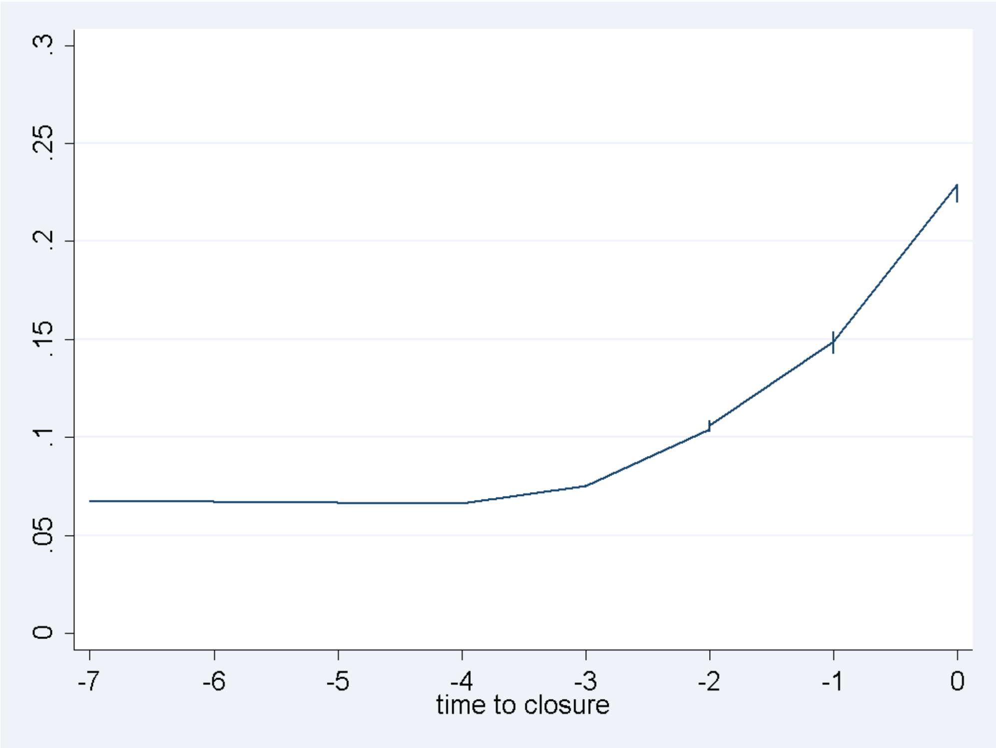
In this section we explore how groups use the internal labor market in response to idiosyncratic shocks leading to a firm or plant closure. We denote as firm/plant closure a situation in which a firm/plant sees its employment drop by more than 90% from one year to the other. Moreover, in order to avoid denoting as a closure a situation in which a firm/plant simply changes identifier, we remove all the cases in which more than 70% of the lost employment ends up in the same firm/plant.

Table 15, column (1)-(7) shows that the excess probability of hiring a worker originating from the group increases when some closures occur in the rest of the group. The effect seem to vanish when the number of closures is high (columns 2, 4 and 6). Moreover, the ILM seems to be more active in the year following the closure (column 3, 4 and 7). Column 8 shows that the excess probability that a worker that finds a job within the group originates from an affiliated firm - over the probability of a worker that finds a job outside the group - increases when the affiliated firm closes. Figure 1 displays the evolution of such an excess probability as time to closure approaches and shows that is starts increasing two years before closure.

These results suggest that a plant/firm closure "activates" the internal labor market, and spurs us to investigate more closely whether the ILM allows to reemploy within the group many of the workers displaced from their job following the closure. To do that, we focus on the workers displaced from firms and plants that close. More precisely, in each year we identify the workers displaced from those plants/firms that in that year undertake their last and last-but-one year of activity. On such a set of job-to-job transitions we compute the excess probabilities as described above. Tables 16 and 17 show the results.

Our inflows table (Table 16) shows that following a plant/firm closure, the probability that an affiliated firm absorbs *displaced* workers originating from the group is 11.5 to 17.7 percentage points higher than the probability to absorb any displaced worker from the external market. Hence, the excess probability of hiring a displaced worker originally employed in the group is larger than the excess probability computed on all workers moving from one job to the other. This confirms that upon a closure event in their group, healthy affiliated firms are even more prone to absorb workers from the ILM with respect to normal times. This is particularly the case when a firm rather than a plant closes within the group. Table 17 focuses on outflows. We find that for displaced workers

Figure 1: Evolution of the excess probability (outflows) as closure approaches.



who land into a group-affiliated firm the probability of originating from a closing firm j within the same group can be as high as 40 percentage points larger than for displaced workers who land outside firm j's group. Then, a large proportion of workers displaced from an affiliated firm/plant is reemployed within the group. These results also suggest that group ILMs play an important role in providing workers with job stability in circumstances where large labor adjustments take place, thereby stimulating workers in investing in group-specific human capital.

5 Conclusions

To be written.

A Appendix

A.1 Estimation of excess probabilities using a different classification of occupations

A.2 Definition of variables

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Table 11: **ILM activity and group sectoral diversification (Inflows)**

Variables	(1)	(2)	(3)	(4)	(5)
(Log) Firm size	0.012***	0.012***	0.012***	0.012***	0.012***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
(Log) Rest of the group size	-0.004	-0.003	-0.003	-0.003	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
(Log) Number of affiliated firms	-0.078***	-0.078***	-0.078***	-0.079***	-0.081***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
State Control	-0.016	-0.016	-0.0013	-0.016	-0.006
	(0.013)	(0.013)	(0.013)	(0.013)	(0.010)
Foreign control	-0.052***	-0.052***	-0.049***	-0.051***	-0.042***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.010)
(Inverse) Diversification (Macrosectors)		**0.005**	**0.007**		
		(0.009)	(0.008)		
(Inverse) Diversification × Rest of the group size			**-0.009**		
			(0.005)		
(Inverse) Diversification (4 digit)				**-0.014***	**-0.025*****
				(0.007)	(0.007)
(Inverse) Diversification × Rest of the group size					**-0.019*****
					(0.003)
N	232,646	232,646	232,646	232,646	232,646
Adjusted R-squared	0.02	0.02	0.02	0.02	0.02
Firm × Group and year fixed effect	Yes	Yes	Yes	Yes	Yes

Note: Dependent variable: Excess probability of hiring a worker if she originates from the same group. *Firm size* is measured by (full time equivalent) total employment; *Rest of the group size* is measured by the (full time equivalent) total employment of all the other firms that are affiliated to the same group as firm j. *State Control* is a dummy variable taking the value 1 if the head of the group is state-owned. *Foreign Control* is a dummy variable taking the value 1 if the head of the group is foreign. *(Inverse) Diversification (macrosectors)* is computed as the sum of the squares of the employment shares of all firms affiliated with a group, where each share is the ratio of the total employment of affiliated firms active in a given macrosectors over the total employment of the group. Macrosectors are agriculture, service, finance, manifacturing, energy, automotive. *(Inverse) Diversification (4-digit)* is computed as the sum of the squares of the employment shares of all firms affiliated with a group, where each share is the ratio of the total employment of affiliated firms active in a given 4-digit sector to the total employment of the group. The variables *Rest of the group size*, *Number of firms in the group*, *(Inverse) Diversification* are normalised to have zero mean. See Appendix A.2 for a detailed description of the variables. One star denotes significance at the 5% level, two stars denote significance at the 1% level, and three stars denote significance at the 0.1% level.

Table 12: **ILM activity and group geographical diversification (Inflows)**

Variables	(1)	(2)	(3)	(4)
(Log) Firm size	0.012***	0.012***	0.012***	0.012***
	(0.002)	(0.002)	(0.002)	(0.002)
(Log) Rest of the group size	-0.004*	-0.001	-0.003	0.001
	(0.002)	(0.002)	(0.002)	(0.002)
(Log) Number of affiliated firms	-0.079***	-0.080***	-0.080***	-0.082***
	(0.005)	(0.005)	(0.005)	(0.005)
State Control	-0.015	-0.007	-0.016	-0.007
	(0.013)	(0.012)	(0.013)	(0.011)
Foreign control	-0.052***	-0.046***	-0.052***	-0.044***
	(0.013)	(0.012)	(0.013)	(0.011)
(Inverse) Diversification (Paris Area)	**-0.029*** **	**-0.010**		
	(0.009)	(0.010)		
(Inverse) Diversification × Rest of the group size		**-0.026*****		
		(0.004)		
(Inverse) Diversification (Regions)			**-0.032*****	**-0.027****
			(0.008)	(0.009)
(Inverse) Diversification × Rest of the group size				**-0.026*****
				(0.004)
N	232,646	232,646	232,646	232,646
Adjusted R-squared	0.02	0.02	0.02	0.02
Firm × Group and year fixed effect	Yes	Yes	Yes	Yes

Note: Dependent variable: Excess probability of hiring a worker if she originates from the same group. *Firm size* is measured by (full time equivalent) total employment; *Rest of the group size* is measured by the (full time equivalent) total employment of all the other firms that are affiliated to the same group as firm j. *State Control* is a dummy variable taking the value 1 if the head of the group is state-owned. *Foreign Control* is a dummy variable taking the value 1 if the head of the group is foreign. *(Inverse) Diversification (Paris Area)* is computed as the sum of the squares of the employment shares of all firms affiliated with a group, where each share is the ratio of the total employment of affiliated firms active in the Paris Area/outside the Paris Area over the total employment of the group. *(Inverse) Diversification (Region)* is computed as the sum of the squares of the employment shares of all firms affiliated with a group, where each share is the ratio of the total employment of affiliated firms active in a given region over the total employment of the group. The variables *Rest of the group size*, *Number of firms in the group*, *(Inverse) Diversification* are normalized to have zero mean. See Appendix A.2 for a detailed description of the variables. One star denotes significance at the 5% level, two stars denote significance at the 1% level, and three stars denote significance at the 0.1% level.

Table 13: **ILM activity and group sectoral diversification (Outflows)**

Variables	(1)	(2)	(3)	(4)	(5)
(Log) Firm size	0.006***	0.006***	0.006***	0.006***	0.005***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
(Log) Rest of the group size	0.002	0.002	0.002	0.001	0.006**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
(Log) Number of affiliated firms	-0.079***	-0.079***	-0.080***	-0.080***	-0.082***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
State Control	-0.002	-0.001	-0.000	-0.001	0.010
	(0.017)	(0.016)	(0.016)	(0.016)	(0.013)
Foreign control	-0.031	-0.030	-0.030	-0.030	-0.020
	(0.018)	(0.018)	(0.017)	(0.017)	(0.014)
(Inverse) Diversification (Macrosectors)		**-0.020****	**-0.018***		
		(0.008)	(0.008)		
(Inverse) Diversification × Rest of the group size			**-0.007***		
			(0.004)		
(Inverse) Diversification (4 digit)				**-0.014**	**-0.027*****
				(0.007)	(0.007)
(Inverse) Diversification × Rest of the group size					**-0.0120*****
					(0.003)
N	225,817	225,817	225,817	225,817	225,817
Adjusted R-squared	0.02	0.02	0.02	0.02	0.02
Firm × Group and year fixed effect	Yes	Yes	Yes	Yes	Yes

Note: Dependent variable: Excess probability of a worker that finds a job in the group to originate from an affiliated firm. *Firm size* is measured by (full time equivalent) total employment; *Rest of the group size* is measured by the (full time equivalent) total employment of all the other firms that are affiliated to the same group as firm j. *State Control* is a dummy variable taking the value 1 if the head of the group is state-owned. *Foreign Control* is a dummy variable taking the value 1 if the head of the group is foreign. *(Inverse) Diversification (macrosectors)* is computed as the sum of the squares of the employment shares of all firms affiliated with a group, where each share is the ratio of the total employment of affiliated firms active in a given macrosectors over the total employment of the group. Macrosectors are agriculture, service, finance, manifacturing, energy, automotive. *(Inverse) Diversification (4-digit)* is computed as the sum of the squares of the employment shares of all firms affiliated with a group, where each share is the ratio of the total employment of affiliated firms active in a given 4-digit sector to the total employment of the group. The variables *Rest of the group size*, *Number of firms in the group*, *(Inverse) Diversification* are normalised to have zero mean. See Appendix A.2 for a detailed description of the variables. One star denotes significance at the 5% level, two stars denote significance at the 1% level, and three stars denote significance at the 0.1% level.

Table 14: **ILM activity and group geographical diversification (Outflows)**

Variables	(1)	(2)	(3)	(4)
(Log) Firm size	0.006***	0.006***	0.006***	0.006***
	(0.002)	(0.002)	(0.002)	(0.002)
(Log) Rest of the group size	0.001	0.004*	0.001	0.007***
	(0.002)	(0.002)	(0.002)	(0.002)
(Log) Number of affiliated firms	-0.080***	-0.081***	-0.081***	-0.083***
	(0.005)	(0.005)	(0.005)	(0.005)
State Control	-0.001	0.009	-0.001	0.012
	(0.016)	(0.015)	(0.016)	(0.014)
Foreign control	-0.032	-0.025	-0.030	-0.021
	(0.018)	(0.017)	(0.017)	(0.015)
(Inverse) Diversification (Paris Area)	**-0.029*** **	**-0.013**		
	(0.008)	(0.009)		
(Inverse) Diversification × Rest of the group size		**-0.027*** **		
		(0.004)		
(Inverse) Diversification (Regions)			**-0.031*** **	**-0.024** **
			(0.008)	(0.008)
(Inverse) Diversification × Rest of the group size				**-0.028*** **
				(0.004)
N	225,817	225,817	225,817	225,817
Adjusted R-squared	0.02	0.02	0.02	0.02
Firm × Group and year fixed effect	Yes	Yes	Yes	Yes

Note: Dependent variable: Excess probability of a worker that finds a job in the group to originate from an affiliated firm. *Firm size* is measured by (full time equivalent) total employment; *Rest of the group size* is measured by the (full time equivalent) total employment of all the other firms that are affiliated to the same group as firm j. *State Control* is a dummy variable taking the value 1 if the head of the group is state-owned. *Foreign Control* is a dummy variable taking the value 1 if the head of the group is foreign. *(Inverse) Diversification (Paris Area)* is computed as the sum of the squares of the employment shares of all firms affiliated with a group, where each share is the ratio of the total employment of affiliated firms active in the Paris Area/outside the Paris Area over the total employment of the group. *(Inverse) Diversification (Region)* is computed as the sum of the squares of the employment shares of all firms affiliated with a group, where each share is the ratio of the total employment of affiliated firms active in a given region over the total employment of the group. The variables *Rest of the group size*, *Number of firms in the group*, *(Inverse) Diversification* are normalized to have zero mean. See Appendix A.2 for a detailed description of the variables. One star denotes significance at the 5% level, two stars denote significance at the 1% level, and three stars denote significance at the 0.1% level.

Table 15: **ILM activity and firm/plant closures in the group**

Variables	Inflows (1)	Inflows (2)	Inflows (3)	Inflows (4)	Inflows (5)	Inflows (6)	Inflows (7)	Outflows (8)
(Log) Firm size	0.012***	0.012***	0.012***	0.012***	0.012***	0.012***	0.012***	0.010***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
(Log) Rest of the group size	-0.004 *	-0.004	-0.003	-0.003	- 0.003	-0.003	-0.004	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002))
(Log) Number of affiliated firms	-0.079***	-0.079***	-0.078***	-0.078***	-0.079***	-0.079***	-0.078***	-0.079***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Firm closure in the rest of the group	**0.007*** **							
	(0.001)							
Exactly 1 firm closure		**0.007*** **						
		(0.001)						
Between 2 and 5 firm closures		**0.007*** **						
		(0.002)						
Between 6 and 20 firm closures		**0.008* **						
		(0.003)						
More than 20 firm closures		**-0.004**						
		(0.016)						
Firm closure at t-1			**0.017*** **					
			(0.001)					
Exactly 1 firm closure at t-1				**0.018*** **				
				(0.001)				
Between 2 and 5 firm closures at t-1				**0.016*** **				
				(0.002)				
Between 6 and 20 firm closures at t-1				**0.020*** **				
				(0.003)				
More than 20 firm closures at t-1				**0.025**				
				(0.021)				
Plant closure in the group					**0.006*** **			
					(0.001)			
Exactly 1 plant closure						**0.005*** **		
						(0.003)		
Between 3 and 5 plant closures						**0.007*** **		
						(0.002)		
Between 6 and 20 plant closures						**0.010*** **		
						(0.002)		
Between 21 and 100 plant closures						**0.009** **		
						(0.003)		
More than 100 plant closures						**0.007**		
						(0.004)		
Plant closure at t-1							**0.015*** **	
							(0.002)	
Own closure								**0.086*** **
								(0.006)
N	232,646	232,646	232,646	232,646	232,646	232,646	232,646	225,817
Adjusted R-squared	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Firm × Group and year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Dependent variable: Columns (1)-(7) Excess probability of hiring a worker if she originates from the same group. Column (8) Excess probability of a worker finding a job in the group to originate from an affiliated firm. *Firm size* is measured by (full time equivalent) total employment; *Rest of the group size* is measured by the (full time equivalent) total employment of all the other firms that are affiliated to the same group as firm j. *Firm closure in the rest of the group* is a dummy variable that takes the value 1 if at least one firm in the rest of the group closes.*Firm closure at t-1* is a dummy variable that takes the value 1 if at least one firm in the rest of the group closes at time t-1. Similarly for plant closure. One star denotes significance at the 5% level, two stars denote significance at the 1% level, and three stars denote significance at the 0.1% level.

Table 16: Inflows - Displaced workers

Year	Mean	St.Err.	Percentiles 50	75	95	N
			Firm closure			
2003	0.13750	0.00396	0	0.00793	1	6127
2004	0.15258	0.00435	0	0.02956	1	5540
2005	0.15824	0.00452	0	0.04741	1	5264
2006	0.16215	0.00460	0	0.04161	1	5261
2007	0.15380	0.00434	0	0.02219	1	5606
2008	0.15616	0.00438	0	0.02272	1	5608
2009	0.17722	0.00492	0	0.09610	1	4856
			Plant closure			
2003	0.11548	0.00285	0	0.00535	1	9614
2004	0.12528	0.00309	0	0.01000	1	8956
2005	0.13273	0.00321	0	0.01784	1	8746
2006	0.13242	0.00318	0	0.01852	1	8780
2007	0.12686	0.00304	0	0.01098	1	9352
2008	0.12369	0.00296	0	0.00714	1	9714
2009	0.14424	0.00351	0	0.03042	1	7912

Table 17: Outflows - Displaced workers

Year	Mean	St.Err.	Percentiles 50	75	95	N
			Firm closure			
2002	0.35036	0.00859	0.07146	0.87500	1	2392
2003	0.40080	0.00948	0.16666	0.98913	1	2091
2004	0.43830	0.01012	0.25000	1	1	1907
2005	0.42275	0.00971	0.22562	0.99969	1	2028
2006	0.40051	0.00935	0.16741	0.99138	1	2147
2007	0.42943	0.00960	0.24608	0.99840	1	2044
2008	0.40475	0.00924	0.20000	0.98477	1	2130
			Plant closure			
2002	0.22774	0.00525	0.00193	0.33333	1	4893
2003	0.24811	0.00569	0.00454	0.47468	1	4499
2004	0.27456	0.00612	0.00588	0.51500	1	4264
2005	0.25895	0.00575	0.00281	0.50000	1	4566
2006	0.25502	0.00564	0.00453	0.50000	1	4670
2007	0.26216	0.00573	0.00507	0.50000	1	4612
2008	0.25304	0.00570	0.00549	0.48033	1	4531

Table 18: Inflows - High-Low Frequencies (Department Restriction)

Year	Mean	St.Err.	50	75	95	N
			Percentiles			
	Unweighted firm-level aggregation					
2003	0.08184	0.00128	0	0.00878	0.61111	30005
2004	0.08563	0.00133	0	0.01033	0.66658	29146
2005	0.08733	0.00131	0	0.01057	0.66667	30689
2006	0.08781	0.00128	0	0.01059	0.66667	32557
2007	0.08030	0.00119	0	0.00658	0.59000	34443
2008	0.07012	0.00098	0	0.00221	0.50000	44642
2009	0.08133	0.00115	0	0.00455	0.64187	38347
2010	0.08001	0.00113	0	0.00333	0.65727	39618
	Firm-level weighted aggregation					
2003	0.07954	0.00127	0	0.01133	0.62500	30005
2004	0.08335	0.00132	0	0.01269	0.66667	29146
2005	0.08445	0.00130	0	0.01338	0.66667	30689
2006	0.08525	0.00127	0	0.01370	0.69231	32557
2007	0.07773	0.00117	0	0.00930	0.59259	34443
2008	0.06762	0.00097	0	0.00350	0.50000	44642
2009	0.07883	0.00114	0	0.00671	0.66471	383487
2010	0.07773	0.00112	0	0.00522	0.66667	39618

Table 19: Outflows - High-Low Frequencies (Department Restriction)

Year	Mean	St.Err.	Percentiles 50	75	95	N
	Unweighted firm-level aggregation					
2002	0.08244	0.00129	0	0.00973	0.62500	29443
2003	0.08781	0.00137	0	0.01396	0.66667	28116
2004	0.09114	0.00137	0	0.01468	0.72549	29188
2005	0.08931	0.00131	0	0.01235	0.70232	31713
2006	0.08297	0.00112	0	0.01057	0.06000	32953
2007	0.07159	0.00100	0	0.00378	0.50000	43192
2008	0.08040	0.00114	0	0.00520	0.59996	38373
2009	0.08274	0.00118	0	0.00588	0.66667	37255
	Firm-level weighted aggregation					
2002	0.07944	0.00128	0	0.01203	0.62500	29443
2003	0.08504	0.00135	0	0.01594	0.66667	28116
2004	0.08768	0.00135	0	0.01694	0.71653	29118
2005	0.08622	0.00129	0	0.01582	0.71429	31713
2006	0.07967	0.00121	0	0.01361	0.60000	32953
2007	0.06868	0.00099	0	0.00515	0.50000	43192
2008	0.07785	0.00113	0	0.00732	0.61097	38373
2009	0.07969	0.00117	0	0.00854	0.66667	37255