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Insurance Between Firms: The Role of Internal Labor Markets

Giacinta Cestone♣, Chiara Fumagalli♦, Francis Kramarz♥ and Giovanni Pica♠

Abstract: We explore how business groups use internal labor markets (ILMs) in response to changing economic conditions. We show that group-affiliated units faced with *positive* shocks to growth opportunities gain market share relying on their ILM to ensure swift hiring, especially of technical managers and skilled blue collar workers. A closer access to the group's human capital facilitates employee relocations in order to fully exploit growth opportunities. *Adverse* shocks affecting one unit in the organization increase workers' mobility to other units in the group rather than to external firms, with stricter employment protection causing an additional increase in internal mobility. Overall, ILMs provide an insurance mechanism between firms in a group, allowing such organizations to bypass hiring and firing frictions; they provide job stability to employees as a by-product.

Keywords: Business Groups, Human Capital, Labor Market Frictions, Internal Labor Markets.

JEL Classification: G30, L22, J20.

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1 Introduction

A long-standing question in economics is how firms adjust and which margins they exploit when business conditions change. A directly related question is whether some types of organizations are better able than others to swiftly adapt to changing economic conditions, in order to thrive in good times and survive in bad times. This paper addresses these questions by investigating the role of Internal Labor Markets (ILMs) in allowing widespread organizations, business groups, to accommodate positive and negative shocks calling for labor adjustments in their units. To the extent that hiring and firing costs affect the external labor market in many countries, labor adjustments may be less onerous to perform within the ILM. Units faced with profitable growth opportunities can swiftly draw on the human capital available elsewhere within the organization, curbing search and training costs; similarly, units hit by an adverse shock can avoid termination costs by redeploying part of their employees to healthier units. Prompted by this argument, the paper explores to what extent business groups use ILMs in response to changing economic conditions; it identifies the labor market frictions that drive the ILM reaction to shocks; it investigates whether access to the ILM allows group members to outperform firms that cannot rely upon the same channel.

In order to address the above issues we identify positive and negative idiosyncratic shocks that hit part of an organization and observe the subsequent employment flows, as well as firms' performance. The data requirements to accomplish this task are heavy. We need to observe the structure of the business organization, i.e. its constituting units; to measure workers' mobility, distinguishing the transitions that occur within the organization from those that do not, as well as the economic situation of the origin and destination units. We are able to rely on unique data sources provided by INSEE that allow us to merge detailed information on the structure of business groups in France with a matched employer-employee data set and administrative fiscal data on balance sheets and income statements for virtually all French firms. We focus here on ILMs within business groups – i.e. networks of independent legal entities ("subsidiaries") controlled by a common owner – which represent an ubiquitous organizational form in both developed and developing economies.[1]

We first study how groups use ILMs when faced with *positive* shocks, namely when a group

[1] Groups account for a large fraction of the economic activity in several countries. Using ownership data on listed companies in 43 countries, Faccio, Mork, and Yavuz (2019) find that the percentage of group affiliated firms ranges between 30 and 50 percent in several countries in Europe, Latin America and Asia (see also Faccio, Lang, and Young (2001) and Masulis, Pham, and Zein (2015)). Prominent examples of groups include Tata (India), Samsung (Korea), Siemens (Germany), Ericsson (Sweden), Fiat Chrysler (Italy), LVMH (France), GE (US), Virgin (UK), News Corp (Australia) and Bradesco (Brasil). Indeed, alongside large renowned groups, which are often multinational enterprises, mid-sized business groups form the productive fabric of many economies. Based on our comprehensive data on both listed *and* private companies, we document that business groups account for 40% of total employment and 60% of value added in the French economy.

subsidiary experiences an unexpected growth opportunity, as captured by the death of a large competitor. More specifically, we conduct an event study exploiting 100 closures of large competitors that occurred in 84 industries in France between 2002 and 2010. To the best of our knowledge, no other paper has exploited large and unanticipated competitor exits as a source of exogenous variation: we do so to study how groups manage their human capital in response to favorable demand shocks.

For each group-affiliated firm active in the positively shocked industries, we identify the set of firms from which our firm of interest actually or potentially hires workers, and compute the flow of workers within each pair of firms in any year. We then study the evolution of firm-to-firm worker flows around the large closure event, in pairs of firms that belong to the same group (the ILM flow) and in pairs that do not (the External Labor Market, or ELM flow).

Our results show that *positive shocks trigger ILM activity*: in each of the three years following a competitor closure event, the fraction of workers absorbed from each ILM partner (relative to the total intake) increases by 15% to 20% with respect to the pre-event baseline. In line with our theoretical predictions, positively shocked firms draw human capital predominantly from group affiliates that display low productivity and poor expansion opportunities in the years leading up to an event. Interestingly, we also find that the ILM effect is mainly driven by the hiring of technical managers (engineers, scientists, and other professionals with technical skills) and skilled blue collars. We interpret this as evidence that ILMs help alleviate search and training costs that are particularly pronounced in the external market for skilled human capital (Abowd and Kramarz (2003), Kramarz and Michaud (2010), Blatter, Muehlemann, and Schenker (2012)).

We also investigate whether ILMs help group-affiliated firms take better advantage of these growth opportunities. This is an important question, in light of early and recent claims that firms' growth may be constrained by human capital frictions (Penrose (1959) and Parham (2017))[2]. We build a measure of *ILM access* for each group-affiliated firm: the employment size of same-group affiliates located within the same *Employment Zone* (local labor market) as the firm, but active in different industries. We then ask whether affiliated firms with better *ILM Access* are more likely to gain market shares following the death of a competitor. We find evidence that this is the case. This suggests that ILMs are an important determinant of organizations' growth that has been overlooked in the literature, where the focus has often been on internal *capital* markets as a gateway to exploit investment opportunities (Giroud and Mueller (2015)).

[2] The idea that a lack of skilled human capital may hamper growth is supported by a strand of literature emphasizing the important role of managers for firm performance (Bertrand and Schoar (2003), Bloom, Sadun, Van Reenen, Lemos, and Scur (2014), Bender, Bloom, Card, Van Reenen, and Wolter (2016)), and by evidence that frictions in the managerial labor market represent an important hurdle to firm expansion (Agrawal and Ljungqvist (2014)).

We then investigate how ILMs allow groups to respond to *negative* shocks, and attempt to identify the associated frictions. To do this, we perform an event study exploiting episodes of closures and mass layoffs involving group-affiliated firms. We compute the employment flows in pairs of firms in which the firm of origin is a group-affiliated firm that will eventually close. We then study the evolution of bilateral employment flows in the run-up to a closure event, in pairs where the destination firm belong to the same group as the closing firm (the ILM flows), and in pairs where destination and origin are not part of the same group (the ELM flows).

Closures (and mass-layoffs) within a group are shown to trigger ILM activity. In the last two years of activity of the closing firm the fraction of displaced workers redeployed to an ILM partner registers a twofold increase (in the year before closure), and a threefold increase (in the closure year) with respect to its 11% baseline, while showing no trend in the preceding years. Which labor market frictions trigger this effect? We show that the closure or downsizing of group units with just more than 50 employees – which according to French labor laws are subject to more stringent labor market regulation – generates a larger ILM response than the closure/downsizing of units with just less than 50 employees. Hence, higher firing costs and greater union power make ILMs more valuable for groups, particularly when faced with potentially large scale separations.[3] Additionally, we find that employees displaced from closing subsidiaries are redeployed, within the ILM, to units that enjoy better growth opportunities and are more productive. We also show that ILMs, as a side-product, provide blue collar and clerical workers with implicit employment insurance through greater job stability within the group.

To the best of our knowledge, this is the first paper that shows that organizations respond to the presence of labor market regulation and hiring frictions in the external labor market by operating ILMs, thereby gaining flexibility in the face of changing economic conditions and the ability to exploit new growth opportunities. We believe that our results are particularly significant since virtually all firms around the world face both hiring and firing frictions.[4]

The paper builds a bridge across several strands of literature. Starting with the work of Doeringer and Piore (1971), the labor/personnel literature has mostly studied the functioning of *vertical* mobility *within firms*. Focusing on promotion and wage dynamics, various authors have argued that ILMs can provide effort incentives, wage insurance against fluctuations in workers' ability, and incentives to accumulate human capital.[5] Our results suggest that these motives explain only in part why orga-

[3] This is consistent with recent evidence that business groups prevail in countries where employment protection regulations are stricter (Belenzon and Tsolmon (2015)).

[4] We discuss the relevance of hiring and firing costs in many countries in Section 2, footnotes 11 and 12.

[5] See, among others, Harris and Holmstrom (1982), and the comprehensive surveys of Gibbons and Waldman (1999), Lazear and Oyer (2012) and Waldman (2012). For more recent contributions to this literature, see Friebel and Raith

nizations operate ILMs. Indeed, we present evidence that *horizontal ILMs* are used to accommodate economic shocks in the presence of labor market frictions.

Within the finance literature, some authors have claimed that business groups fill an institutional void when external labor and financial markets display frictions (Khanna and Palepu (1997), Khanna and Yafeh (2007)). Several papers have emphasized the role of internal *capital* markets in groups, showing that access to a group's internal finance makes affiliated firms more resilient to adverse shocks with respect to stand-alone firms (e.g. Almeida, Kim, and Kim (2015), Boutin, Cestone, Fumagalli, Pica, and Serrano-Velarde (2013), Maksimovic and Phillips (2013), Manova, Wei, and Zhang (2015), Urzua and Visschers (2016)). Giroud and Mueller (2015) provide evidence that, by alleviating financial constraints, internal capital markets also allow conglomerates to take better advantage of positive shocks to investment opportunities.[6]

In contrast with the internal capital market literature, research on internal *labor* markets is more limited: no prior work seems to have studied how organizations use their ILMs to accommodate positive shocks to investment opportunities in the presence of labor market frictions.[7] We fill this gap by providing novel results. First, we present direct evidence that group-affiliated firms faced with growth opportunities draw on their group's ILMs to hire skilled human capital, which points to hiring frictions as an important determinant of ILM activity. Second, we show that the group units with closer geographical access to the ILM gain market share (with respect to those without such access) when faced with growth opportunities, suggesting that the ILM mitigates human capital scarcity that hinders growth. Our results on the response to *adverse shocks* are instead related to work by Tate and Yang (2015), who provide evidence that multi-divisional firms use ILMs when coping with plant closures. We add to their paper by investigating for the first time which frictions cause ILM activity in response to adverse shocks, identifying employment protection regulation as a major underlying driver, and studying the employment insurance implications for workers. Importantly, our paper shows that ILMs do not just have value in bad times, when a workforce reduction is called for; indeed, by studying the hiring behavior and the performance of different group units subject to a *positive* demand shock, we show that access to the ILM is also critical in good times, allowing groups to better take advantage of expansion opportunities.

(2013), Ke, Li, and Powell (2018) and Kostol, Nimczik, and Weber (2019).

[6]Giroud and Mueller (2015) find that this internal capital market activity manifests itself in increased investment and employment in the positively shocked units in the conglomerate. However, as they do not use employer-employee data, they cannot study whether human capital is reallocated towards these units through the ILM or the external labor market.

[7]Faccio and O'Brien (2016) show that employment in group-affiliated firms (as opposed to stand-alone firms) is less sensitive to business cycle fluctuations, which suggests that groups manage their workforce differently. They rely on a cross-country firm level database and differently from us, they do not have employer-employee data, hence ILM activity cannot be directly documented and analyzed.

Our findings suggest that along with internal capital markets, ILMs represent a channel that makes diversified organizations better equipped to withstand challenges and seize opportunities, relative to stand-alone companies.[8] We also establish that ILMs operate within networks of firms that are separate legal entities, as is the case in business groups, where the benefits derived from actively reallocating human resources across subsidiaries must be traded off against various hurdles, such as minority shareholder protection, contractual costs, and the fear of "piercing the corporate veil" between parent and subsidiary.[9] In this respect, our paper also speaks to recent work that investigates the costs and benefits of organizing production within business groups as opposed to multi-divisional firms (Belenzon, Berkovitz, and Bolton (2009), and Luciano and Nicodano (2014)).

In addition, this paper is related to a growing literature that explores how firms organize production in hierarchies to economize on their use of knowledge (Garicano (2000)). Caliendo and Rossi-Hansberg (2012) predict that firms which grow substantially do so by adding more layers of management to the organization.[10] Our findings suggest that when faced with expansion opportunities, group-affiliated firms draw on the group's ILM to economize on the costs associated with hiring employees in the top layers of the organization (technical managers) and other high-knowledge occupations. This is also consistent with the idea that business groups are common pools of specific knowledge capital that can be shared across different subsidiaries (see Altomonte, Garicano, Ottaviano, and Rungi (2017)).

Finally, our work contributes to a line of research looking at how firms provide employment insurance to workers (see Sraer and Thesmar (2007) and Ellul, Pagano, and Schivardi (2015)). We add to this literature by investigating how ILMs allow business groups to protect employment when faced with shocks. Another closely related line of research has asked whether firms provide *wage* insurance to workers against both temporary and permanent shocks (Guiso, Pistaferri, and Schivardi (2005)). The question of whether diversified groups are better able to provide wage insurance to their workers lies beyond the scope of this paper, and is among the next steps in our research agenda. However, we present some elements showing that, in groups hit by a negative shock, displaced workers' hourly wages tend to be insured while hours of work are not.

The paper proceeds as follows. Section 2 lays out a series of empirical predictions. In Section 3 we describe the data and present descriptive evidence on ILM activity within groups. We present

[8]See "From Alpha to Omega" *The Economist*, 15 August 2015, on how "a new breed of high-performing conglomerates" is challenging the view that diversified groups are bound to do worse than their focused counterparts.

[9]The regulation of liability within corporate groups differs substantially across countries (see Hopt (2015)). In some jurisdictions, including France, it is common to hold the parent liable vis-a-vis its subsidiaries' debt holders if the parent interfered in the management of the subsidiaries, e.g. by reallocating resources across them.

[10]Using French data, Caliendo, Monte, and Rossi-Hansberg (2015) find evidence that French manufacturing firms grow by actively managing the number of layers in their organization in a way that is consistent with these predictions.

our empirical strategy and discuss results on the ILM response to positive shocks in Section 4, and to negative shocks in Section 5. Section 6 concludes.

2 Theoretical Background

Internal labor markets may emerge within organizations as a potential response to frictions that hinder labor adjustments made on the external labor market. In this section we lay out how an optimally run ILM can create value in complex organizations (business groups, in our paper), by saving on labor adjustment costs, and enabling a more flexible response to shocks with respect to stand-alone firms. In Appendix A.1, we provide a simple model and the formal derivations to sustain our claims.

Consider a firm hit by an idiosyncratic shock ε and faced with (potential) hiring and firing costs. Previous work has documented that firing costs are substantial in many countries, including France.[11] Furthermore, several papers have estimated that hiring costs amount to a non negligible fraction of the wage bill in many economies.[12] Abowd and Kramarz (2003), Kramarz and Michaud (2010) show that hiring and firing costs appear to comprise a fixed and a linear component (in the size of the adjustment). For expositional purposes, we focus on the latter component and assume that the firm bears a hiring cost H for each newly hired employee, and a firing cost F for each dismissed worker.

As shown in Appendix A.1, a stand-alone firm adjusts employment only when the magnitude of the shock is large enough. Hence, stand-alone firms are optimally inactive when the shock is within a $\{\varepsilon_L, \varepsilon_H\}$ band, in which case they incur no hiring or firing cost but have a marginal productivity of labor that differs from the workers' wage. Put differently, when $\varepsilon > 0$ but small enough these firms forfeit growth opportunities, while when $\varepsilon < 0$ but small enough they are inefficiently retaining redundant workers (see Bentolila and Bertola (1990) for an early exposition.)

Assume now that the firm hit by the idiosyncratic shock is affiliated with a business group. The firm has an additional margin of adjustment: it can absorb or redeploy workers using the group's

[11] The OECD reports that in most countries in Europe and in several Asian countries protection against individual dismissals is at least as stringent as in France. Protection against collective dismissals can be restrictive even in countries with lighter constraints on individual dismissals, such as Canada, Japan and Mexico (see OECD (2013)). While the US has probably the softest protection against *individual* dismissals, wrongful discharge laws do affect US companies in various ways: their impact on employment, productivity, firm entry and even capital structure decisions has been largely documented (see Autor, Donohue II, and Schwab (2006), Autor, Kerr, and Kugler (2007)). Additional costs for US firms originate from federal and state legislation imposing advance notice requirements in case of mass layoffs: this is reflected in an index for collective dismissals close to the OECD average.

[12] See Manning (2006), Abowd and Kramarz (2003), Kramarz and Michaud (2010), Dube, Freeman, and Michael (2010), Blatter, Muehlemann, and Schenker (2012) and Muehlemann and Pfeifer (2016) for studies using data from the UK, France, California, Switzerland and Germany. However, these papers only focus on recruitment and (in some cases) training costs, while ignoring indirect hiring costs such as the cost of having unused capital when there is an unfilled vacancy as highlighted by Manning (2011); or the cost of missing growth opportunities when the firm cannot hire the right type of workers.

internal labor market at lower costs. Indeed, if a *positive shock* calls for an expansion of the labor force, search and training costs that arise in the external labor market can be mitigated within the ILM. For example, the ILM is likely to suffer less from information asymmetry concerning workers' characteristics (Greenwald (1986) and Jaeger (2016)), and may perform better than the external labor market in matching a vacancy with the specific skills required. Furthermore, training costs are lower for workers absorbed from the ILM whenever there is a group-specific human capital component. Analogously, when a *negative shock* calls for downsizing a group unit, firing costs can be bypassed altogether or alleviated by redeploying workers to other group units through the ILM. For instance, dismissals can be turned into costless voluntary separations by offering workers an alternative job within the same group. Furthermore, in some employment protection systems, transfers across firms affiliated with the same group are not treated as dismissals provided they fall below a given distance threshold (see Belenzon and Tsolmon (2015)). Also, in case of collective terminations involving more complex employment protection procedures, labor law demands can be met more easily by redeploying (part of) the dismissed workers within the group's ILM.

In the Appendix, we focus on a two-unit group. We normalize the cost of ILM adjustments to zero, while $H > 0$ and $F > 0$ capture the additional adjustment costs encountered on the external market. We study the optimal adjustment policy of the group, and show that optimality conditions entail equalizing the marginal productivity of labor across individual group units. We show that the group resorts first to the ILM, moving workers towards (away from) the positively (negatively) shocked unit, and only combines the ILM reaction with external adjustments when faced with large enough shocks (see Proposition 1 in the Appendix).[13] Hence, an idiosyncratic shock hitting a group unit spurs an activation of the internal labor market; this ILM reaction is more intense when external frictions are more severe.

To summarize the lessons of our theoretical analysis, in the presence of labor market frictions, the ability to use the ILM in response to a shock adds value to the group in two ways (see Corollary 2): (*i*) by granting flexibility, i.e. the ability to adjust the labor force more than stand-alone firms, thereby benefiting from a more efficient allocation of labor across the affiliated units when faced with positive or negative shocks, and (*ii*) by allowing to save on firing/hiring costs. Of course, some inefficiency is borne by the other (non shocked) units in the organization, that may end up employing an excessive amount of workers in case of a negative shock, and may lose workers whose marginal productivity is larger than the wage in case of a positive shock. However, it must be emphasized

[13]Proposition 1 also shows that a small cost of ILM reallocation is enough to prove that only the shocked unit adjusts on the external labor market.

that the optimal ILM allocation ensures that the savings in adjustment costs in the shocked unit more than compensate the efficiency loss borne by the other group units. The internal labor market creates value by allowing different units within the same organization to provide each other with mutual insurance against shocks that, otherwise, would call for costly external labor adjustments.

3 Data and Descriptive Statistics on ILM Activity

3.1 The data

Exploring empirically whether affiliated firms disproportionately rely on their group ILM to adjust their labor force in response to shocks requires detailed information on both workers and firms. First, we need to observe labor market transitions, i.e. workers' transitions from firm to firm. Second, for each firm, we need to identify the entire structure of the group this firm is affiliated with, so as to distinguish transitions originating from (landing into) the firm's group versus transitions that do not originate from (land into) the group. Third, we need information on firms' characteristics. We obtain this information for France putting together three data sources from INSEE (*Institut National de la Statistique et des Études Économiques*).[14]

Our first data source is the DADS (*Déclarations Annuelles des Données Sociales*), a large-scale administrative database of matched employer-employee information. 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 information on age, gender, the number of days during the calendar year that individual worked in that plant, the type of occupation (classified according to the socio-professional categories described in the Appendix, Table A1), the full time/part time status of the employee and the (gross and net) wage. Moreover, the data set provides the fiscal identifier of the firm that owns the 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 DADS Postes, the version of the DADS we work with, is not a full-fledged panel of workers: in each annual wave the individual identifiers are randomly re-assigned. Nevertheless, we are able to identify workers' year-to-year transitions as each wave includes not only information on

[14]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.

the individual-plant relationships observed in year t, but also in year $t-1$. Hence, this structure allows us to identify workers transiting from one firm to another across two consecutive years.[15]

The identification of business group structures is based on the yearly survey run by INSEE called LIFI (*Enquête sur les Liaisons Financières entre sociétés*), our second data source. The LIFI 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 holds at least 50% of the voting rights in another firm's general assembly. This is in principle a tight threshold, as in the presence of dispersed minority shareholders control can be exercised with smaller equity stakes. However, we do not expect this to be a major source of bias, as in France most firms are private and ownership concentration is strong even among listed firms.[16] To sum up, for each firm in the French economy, LIFI enables 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 third data source we rely upon is FICUS, which contains information on firms' balance sheets and income statements. It is constructed from administrative fiscal data, based on mandatory reporting to tax authorities for all French tax schemes, and it covers the universe of French firms, with about 2.2 million firms per year. FICUS contains accounting information on each firm's assets and financials, as well as capital expenditure, cash flows and interest payments.

The data span the period 2002-2010. We remove from our samples the occupations of the Public Administration (33, 45 and 52 in Table A1, Appendix A.2) because the determinants of the labor market dynamics in the public sector are likely to be different from those of the private sector. We also remove temporary agencies and observations with missing wages. Finally, we also remove from the data set those employers classified as "*employeur particulier*": they are individuals employing workers that provide services in support of the family, such as cleaners, nannies and caregivers.[17]

[15] 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.

[16] Bloch and Kremp (1999) document that in large private companies the main shareholder's stake is 88%. Ownership concentration is slightly lower for listed companies, but still above 50% in most cases.

[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 is incorrect.

3.2 Descriptive evidence on ILM activity

Our data set comprises, on average, about 1,574,000 firm-to-firm workers transitions per year during the sample period. Out of those, 800,000 workers each year make a transition to a group-affiliated firm, and about 200,000 originate from a firm affiliated with the same group as the destination firm. Thus, approximately, one worker out of 4 hired by a group-affiliated firm was previously employed in the same group. This 25% is a sizeable figure if contrasted with the negligible probability of coming from a firm of the same group, had the worker been randomly chosen (the average group employs a workforce equal to 0.005% of the total number of employees in the economy).

However, documenting that a large proportion of the workers hired by an affiliated firm was previously employed in the same group is not *per se* evidence that ILMs function more smoothly than external labor markets: intra-group mobility may be high simply because groups are composed of firms that are geographically close to each other, or intensive in occupations among which mobility is naturally high. In other words, group structure may be endogenous (in terms of both occupations and locations) and may affect within-group mobility patterns. Therefore, to provide meaningful descriptive evidence that the ILM facilitates within-group mobility, one should analyse workers' mobility patterns controlling for the firm-specific (possibly time-varying) "natural" propensity of firms to absorb workers transiting between given occupations and locations. We do so first looking at all job movers, and then progressively conditioning on the characteristics of the occupations and the locations of origin and destination.

More formally, we consider a set c of workers – that we sequentially narrow down from all job movers in the economy to all those moving between two specific locations; all those moving between two specific occupations; and, finally, all those moving between two specific pairs of occupations $\times$ locations – and analyse the following linear model for the probability that worker i, belonging to the set c, finds a job in group-affiliated firm j at time t:

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

where $E_{i,c,k,j,t}$ takes value one if job mover i in set c, moving from firm of origin k finds a job in firm j at time t, and zero if she finds a job in any other firm. $BG_{i,k,j,t}$ takes value one if worker i's firm of origin k belongs to the same group as destination firm j, and zero otherwise. The term $\beta_{c,j,t}$ is a firm/job-mover-set specific effect that captures the time-varying natural propensity of firm j to absorb job movers in set c: as will be clear in the next paragraph, it accounts for the fact that at time t firm j may be particularly prone to hire workers moving between given occupations or/and locations. The parameter $\gamma_{c,j,t}$ measures the *excess probability* that, conditional on belonging to the set c, worker i finds a job in firm j if the firm of origin k is affiliated with the same group as j, as compared to a similar worker originating from some firm k outside the group.[18] The error term $\varepsilon_{i,k,j,t}$ captures all other factors that affect the probability that such a worker finds a job in firm j, and is assumed to have, conditional on observables, zero mean.

We estimate equation (1) using a formulation described in Appendix A.3 similar to Kramarz and Thesmar (2013) and Kramarz and Nordström Skans (2014). We first allow c to be the set of *all* job movers in the French economy and, thus, estimate one "unconditional" excess probability for each BG firm at time t: Table 1 shows that these are about 5 percentage points for the average group-affiliated firm.

The role of locations and occupations – Next, we focus on locations. In Panel (a) of Table 2, we estimate equation (1) re-defining c as the subset of job movers transiting to local labor market l from local labor market m; in other words, we compute excess probabilities $\gamma_{c,j,t}$ controlling for a firm of destination $\times$ local labor market pair specific effect: this accounts for the fact that group-affiliated firm j may be particularly prone to absorb workers moving between two given locations.[19] In this case for each BG firm j at time t we estimate as many $\gamma_{c,j,t}$ as local labor market pairs. Aggregating the estimated $\widehat{\gamma}_{c,j,t}$ at the firm-level taking simple averages, we find excess probabilities of a similar magnitude as the "unconditional" ones. When we focus on transitions *within* the same local labor market ($l = m$), excess probabilities are slightly higher (about 6.2 percentage points, see Panel (b)), suggesting that *geographical proximity favors ILM hiring* more than external hiring.

To examine the role of occupations, we compute excess probabilities $\gamma_{c,j,t}$ defining c as the subset of job movers transiting between occupation o and occupation z; hence, $\beta_{c,j,t}$ is a now a destination firm $\times$ occupation-pair effect (Panel (c), Table 2). Aggregating at the firm level, we find that, for the average firm, the excess probability is about 9.5%, thus higher than the "unconditional" probability estimated without controlling for occupation-pair effects. This means that ILM activity is more limited for those occupations that experience the largest flows in the economy, namely non-managerial occupations, as confirmed by Tables 3 and 4 discussed in the next paragraph.[20] Average

[18] By definition, the parameter $\gamma_{c,j,t}$ is identified only for BG-affiliated firms of destination, because there is no variation in $BG_{i,k,j,t}$ for non BG-affiliated firms.

[19] Based on commuting data, the INSEE partitions France into 348 local labor markets ("zones d'emploi" or ZEMP). Due to the high number of ZEMPs, computational hurdles prevent us from estimating $\gamma_{c,j,t}$ for each ZEMP pair $\times$ firm combination. Thus, for each destination firm j in ZEMP l we compute excess probabilities for the case where the ZEMP of origin is the same as the ZEMP of destination ($m = l$) and for the case $m \neq l$. It is however possible to estimate $\gamma_{c,j,t}$ for each geographical department-pair $\times$ firm combination, as there are only 96 departments in France: average excess probabilities have similar magnitudes.

[20] One can show that the "unconditional" excess probability is a weighted average of the $\gamma_{c,j,t}$ estimated at the occupation pair-firm level, with higher weights assigned to occupation pairs that experience relatively larger flows. As the excess probabilities estimated at the occupation pair-firm level $\widehat{\gamma}_{c,j,t}$ turn out to be lower for occupations

excess probabilities remain high (just above 7 percentage points, Panel (d) of Table 2) even when we focus on transitions between the same occupations of origin and destination, i.e. ruling out all the transitions up or down the career ladder suggesting that *internal careers explain only in part why groups operate ILMs.* Furthermore, substantial ILM activity takes place even when accounting for firms natural propensity to hire workers transiting between specific occupation×locations pairs. Indeed, excess probabilities are about 10 percentage points when we control for firm of destination × local labor market pair × occupation pair specific effects (Panel (e)); and about 8 percentage points (Panel (f)) when we focus on job movers transiting between the same occupations *and* locations of origin and destination.

The role of detailed occupations and group characteristics – We then explore whether our estimated excess probabilities $\widehat{\gamma}_{c,j,t}$, defined for a given occupation pair $\{o, z\}$ and firm j in year t, vary by detailed occupations. To do so, using the two-digit classification of occupations provided in the DADS (Table A1, Appendix A.2), we build four broad occupational categories: (*i*) managers, engineers, and professionals; (*ii*) intermediate professions; (*iii*) clerical support, services, and sales workers; (*iv*) blue-collars. Table 3 ranks two-digit occupation categories by ILM activity, as measured by estimated excess probabilities $\widehat{\gamma}_{c,j,t}$. Results suggest that ILM activity varies significantly across occupational categories, and is most intense for managers, engineers, and professionals. The same pattern emerges in Table 4 controlling for firm- and group-level time-varying confounders, time dummies and firms × group fixed effects (column 1). Even when focusing on horizontal job moves, we observe a *more intense ILM activity for managerial occupations* (columns 2 and 3).

The numbers presented in Tables 1 and 2 display an enormous amount of heterogeneity across firms. In particular, the estimated ILM parameter aggregated at the firm-level ($\widehat{\gamma}_{j,t}$) is positive only for firms belonging to the top quartile or decile of the distribution: clearly, not all group-affiliated firms rely on their ILMs. This should not be surprising given the large heterogeneity within the population of French groups. There are relatively few, very large groups, with many large affiliates that are diversified both from a sectoral and geographical perspective; and many small groups, with a small number of affiliates, that are hardly diversified.[21] In Appendix Table A3 we study how firm-level excess probabilities relate to group diversification, controlling for firm- and group-level time-varying confounders, time dummies and firms × group fixed effects. Indeed, *diversification*

that experience relatively larger flows in the economy (e.g., non-managerial occupations, see Tables 3 and 4), the "unconditional" excess probability disproportionately reflects the limited ILM activity for these occupations.

[21]We have ranked French groups based on their size, as measured by full-time equivalent employment. Groups belonging to the top decile of the group-size distribution have on average 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 on average 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.

both across industries and across geographical areas is associated with more intense ILM activity, more so in larger groups. A priori, diversification allows group units to be exposed to unrelated sectoral/regional shocks, thus creating more scope for co-insurance to be provided via the horizontal ILM. On the other hand, conditional on a shock hitting a group member, moving workers across more distant industries/geographical areas is more difficult, due to sector-specific skills, trade union resistance, or labor market regulation. Our results suggest that the former effect prevails, the more so in large groups where the internal labor market is thicker and the array of skills available wider.

To sum up, our descriptive evidence suggest that French business groups operate ILMs and that the accommodation of shocks, exploiting between-firms diversification, may be a major driver of this activity. In the next two sections we rely on well-measured positive and negative shocks to precisely assess whether ILM activity intensifies in good (Section 4) and bad (Section 5) times and to study the subsequent effect on firm and worker outcomes.

4 The ILM Response to Positive Shocks

In this Section we explore whether group firms faced with a positive shock – the collapse of a large industry competitor – rely on the ILM to adjust their labor force.

For this purpose we identify closures of large competitors that occurred in France between 2002 and 2010. We define as "closures" all episodes in which a firm experiences a drop in employment from one year to the next of 90% or more during our sample period. In order to eliminate false closures, i.e. situations in which firms simply change identifier relabeling a continuing activity (such as in the case of an acquisition), we exploit the matched employer-employee nature of our data and remove all the cases in which more than 70% of the lost employment ends up in a single other firm.[22] The closure rates that we find (see Table A4 in Appendix A.4), their evolution over time and their heterogeneity across firms of different size is consistent with an extensive study from INSEE on closures in the French economy (Royer (2011)). For the purpose of the analysis in this Section, we focus on closures of large firms, defined as firms with more than 500 workers – on average – in normal times, i.e. at least 4 years prior to the closure event. Tables A5 to A7 in Appendix A.4 report the industries in which the large closures occur (the shocked industries), the closure year and the size of the closing firm in normal times.

In the baseline analysis, we focus on 84 industries with either a single large closure or multiple closures occurring in the same year, accounting for 100 large closure events in total. In Appendix

[22]Our results are robust to a stricter definition of closures, in which we regard as false closures all cases in which 50 percent of the lost employment ends up in a single other firm. See Table 5.

Table A11 we check that our results are robust to including industries with multiple non-simultaneous closures. We identify all the group-affiliated firms that operate in the shocked industries. For each of them, denoted as firm j, we identify the set of labor market partners, i.e. all the firms from which firm j actually or potentially absorbs workers.[23] We then compute the bilateral employment flows within each pair of firms in each year, which can be either positive or zero. Our unit of observation is thus a pair – firm of origin/destination firm – in a given year, in which the firm of destination is a group affiliated firm that operates in one of the shocked industries. Our baseline sample consists of 2,978,549 pair-year observations, out of which 60,754 are same-group pairs and 2,917,795 are external pairs (see Table A8 in Appendix A.4).

To study the evolution of the bilateral flows of workers, before and after the shock, we implement a pooled event study exploiting the staggered nature of our large closure events. We denote as 0 the year of the positive shock, i.e. the first year in which the large competitor is no longer active in a given industry, and we build a three-year window around the event. Initially, we focus on worker flows from same-group partners, and estimate the following equation:

$$f_{j(s)kt} = \phi_{j(s)k} + \beta_t + \sum_{\tau=-3}^{+3} \alpha_\tau^{Int} I_{\tau st}^{Int} + \varepsilon_{j(s)kt} \qquad (2)$$

where $f_{j(s)kt}$ is the ratio of workers hired by BG-affiliated firm j (active in shocked industry s) from affiliated firm k in year t, to the total number of firm-to-firm movers hired by firm j in year t. This initial specification includes only pairs in which the firm of origin k is affiliated with the same group as the firm of destination j. The treatment indicator $I_{\tau st}^{Int}$ equals 1 if year t is τ years away from the shock in industry s. We include a set of calendar year indicators β_t in our specification, and firm-pair fixed effects $\phi_{j(s)k}$ that control for all time-invariant unobservable pair characteristics that potentially affect the intensity of the bilateral flows. We cluster standard errors by industry, which is the level at which the shock takes place, and (destination) group. Our standard errors, therefore, allow firm-to-firm flows to be correlated both within industries and within the group shocked firms are affiliated with (i.e. the destination group).

We fix the group each firm is affiliated with based on the affiliation status one year before the event. We do so to address the concern that the event may affect the group structure.[24] By making

[23] We consider a labor market partner any firm that in at least one year has been the origin of at least one employee hired by firm j. Firms of origin affiliated with the same group as firm j are referred to as "same-group firms of origin" or "ILM firms of origin", while the others as "external firms of origin".

[24] Imagine that, following a positive shock to BG firm j, the group decides to acquire a firm that has always had a strong labor flows link with firm j: in this case, the observed increase in internal flows should not be attributed to the activation of the ILM channel.

the identity of the head of the group time-invariant, the firm-pair fixed effects also control for the time-invariant unobservable characteristics of the destination group.

The estimated coefficients $\widehat{\alpha}_\tau^{Int}$ measure how much the average internal flows τ years away from the event differ from the counterfactual flows, approximated in equation (2) by the internal flows outside the $[-3, +3]$ event window. The difference-in-difference estimate between event date -1 and τ is then calculated as $\widehat{\alpha}_\tau^{Int} - \widehat{\alpha}_{-1}^{Int}$. As usual, the difference-in-difference approach identifies the causal effect of a large closure event under the assumption that firm-to-firm flows in treated and untreated pairs would move in parallel in the absence of the shock. While this assumption cannot be tested directly, the leading terms will provide us with an useful indication of its plausibility.

Panel (a) of Figure 1 reports the estimated $\widehat{\alpha}_\tau^{Int} - \widehat{\alpha}_{-1}^{Int}$ together with 95% confidence bands. The leading terms show no indication of pre-existing trends before treatment. Starting from $\tau = 0$, internal flows significantly increase relative the year before the event, by half a percentage point at $\tau = 0$, by more than 1.1 percentage points at $\tau = +1$, and by more than 1.5 percentage points at $\tau = +2$ and $\tau = +3$. Given that average internal flows in the pre-event window amount to 7.4% (Table A9, Appendix A.4), on average the shock raises internal flows by about 6.8% at $\tau = 0$, about 15% at $\tau = +1$, and about 20% at $\tau = +2$ and $\tau = +3$.

To contrast the ILM reaction with the external labor market (ELM) response, we estimate a more general specification that includes also pairs in which the firm of origin k is not necessarily affiliated with the same group as the firm of destination j, as firm k may now also be affiliated with another group or be a stand-alone firm:

$$f_{j(s)kt} = \phi_{j(s)k} + \beta_t^{Int} + \beta_t^{Ext} + \sum_{\tau=-3}^{+3} \alpha_\tau^{Int} I_{\tau st}^{Int} + \sum_{\tau=-3}^{+3} \alpha_\tau^{Ext} I_{\tau st}^{Ext} + \varepsilon_{j(s)kt}, \tag{3}$$

As both internal and external flows are now subject to treatment, equation (3) includes separate treatment indicators for internal and external flows $I_{\tau st}^{Int}$ and $I_{\tau st}^{Ext}$, and allows for different cyclicality of internal and external flows adding separate sets of calendar year dummies β_t^{Int} and β_t^{Ext}. The term $\phi_{j(s)k}$ is, as before, a firm-pair fixed effect that controls for the time-invariant unobservable characteristics of the pair of firms and the destination group they are affiliated with.[25] Standard errors, again, allow the error term to be correlated both within industries and within the (destination) group.

In addition to normalized coefficients for the internal flows ($\widehat{\alpha}_\tau^{Int} - \widehat{\alpha}_{-1}^{Int}$, blue dots), Panel (b) of

[25] Notice that, for a given pair of firms, belonging or not to the same group is a fixed characteristic, given that the affiliation status is fixed one year before the event. Thus, the pair fixed effect also controls for the different intensity of the flows across same group vs non-same group pairs at baseline.

Figure 1 plots the estimated normalized coefficients for the external flows ($\widehat{\alpha}_{\tau}^{Ext} - \widehat{\alpha}_{-1}^{Ext}$, red squares), together with 95% confidence bands. While ILM flows respond to the event, ELM flows do not appear to do so.

To the extent that some groups are concentrated in one geographical area or one industry, the ILM response to the event may simply reflect the fact that group units face lower hiring and training costs when hiring locally and/or within the same industry. To explore whether this is the explanation for our result, we estimate a specification in which we distinguish worker flows (be them internal or external flows) that originate from firms that operate in a different local labor market than firm j and flows that originate from firms that operate in the same local labor market as firm j. Along the same lines, we estimate another specification in which we distinguish flows that originate from firms that operate in a different 4-digit industry than firm j and flows that originate firms in the same 4-digit industry as firm j. Figure 2 shows the results. In particular, panels (a) and (c) show that the evolution of worker flows from ILM and external partners operating in a different local labor market or in a different 4-digit industry than firm j are similar to those of our baseline specification. Hence, the ILM response is positive and significant even across group members that are not homogeneous in terms of industry and geographical area, which confirms that same-group affiliation is *per se* a factor facilitating labor mobility across two firms. Results are also very similar when we study worker flows from firms operating in the *same* local labor market (Figure 2 panel (b)). Instead, and not surprisingly, we find that ILM flows from group units that operate in the same (positively shocked) 4-digit industry as firm j do not show a clear response (Figure 2, panel (d)). This result is in line with our model: an optimal ILM transfers workers to units that are experiencing a positive shock from units that are *not* experiencing the same shock. It also confirms that diversification is actually key to ILM activity.

In Table 5 we perform some robustness checks. Columns (3) and (4) report the estimated coefficients $\widehat{\alpha}_{\tau}^{Int} - \widehat{\alpha}_{-1}^{Int}$ and $\widehat{\alpha}_{\tau}^{Ext} - \widehat{\alpha}_{-1}^{Ext}$ when we control for sectoral trends. In Columns (5) and (6) large closure events are identified based on a more restrictive definition of firm closures: we label as "false closures" all cases where more than 50% of the lost employment ends up in another single firm.[26] Columns (7)-(8) report results obtained when we focus on the $[-2, +2]$ years event window. In all these specifications the results are similar to those in the baseline, reported in columns (1) and (2). In Appendix Table A11, we verify that our results are robust to the inclusion of industries that

[26]The more restrictive definition of firm closures scarcely affects the identification of large closures and our set of shocked industries: the set of industries with a single large closure or multiple closures in the same year loses 3 elements and includes 81 industries (instead of 84). The other more extended sets of industries, including multiple non-simultaneous closures, lose 5 elements each.

experience multiple closures taking place in different years over the sample period; we also investigate robustness to an asymmetric event window. The results are qualitatively similar to the baseline, however the presence of non-simultaneous events makes the estimates less precise.[27]

4.1 ILM access and group firms performance around the event

We now examine whether access to their ILM allows group subsidiaries to better exploit positive shocks to their investment opportunities. Recent empirical evidence suggests that human capital frictions play a role as important as financial frictions in constraining firm's growth (Parham (2017)).[28] Hence, thanks to their ability to draw on the group's human capital, group-affiliated firms should be better placed than their stand-alone rivals to expand and gain market share when faced with a competitor's death.

To explore this issue we study the evolution of firms' outcomes around the event in group-affiliated firms that enjoy different levels of access to the group's human capital, i.e. subject to different ILM frictions. The geographical distance between group units is probably the most important determinant of frictions within the ILM. First, in most employment systems including France, a worker relocation across different sites is more likely to be challenged and to trigger a relocation allowance when it falls beyond a reasonable commuting distance from the current site.[29] Second, geographical proximity between different subsidiaries may facilitate prior communication, which in turn reduces information asymmetry on workers' characteristics. Hence we build, for each group-affiliated firm j subject to a positive shock, a measure of *ILM Access* equal to the employment (measured at $\tau = -1$) of all group subsidiaries affiliated with j and located within the same local labor market (*Zone d'Emploi*), but not in the same 4-digit industry as j.[30]

More in detail, we move to a dataset in which each observation is a group-affiliated firm in a

[27]To further assess the robustness of our results, we adopt the approach proposed by de Chaisemartin and D'Haultfoeuille (2019) who show, in the context of models incorporating group and time effects, that estimates of average treatment effects can be biased if the effects are heterogeneous across groups and time periods. They propose a new estimand based on a variant of the standard common trends assumption. In unreported results we implement the proposed estimand running a simplified version of equation (3) and find that results carry over to this extension.

[28]The idea that lack of skilled workers is another major hurdle for firm growth is supported not only by the strand of literature emphasizing the important role of managers for firm performance and expansion (see footnote 2) but also by growing anecdotal evidence suggesting that firms are struggling to hire and train skilled blue collars workers as much as Stem professionals. See "Hunt for Skilled Labour: 'New Collar' jobs prove hard to fill," *Financial Times*, 30 July 2018, but also: "American Factories Could Prosper if They Find Enough Skilled Workers," *The Economist*, 12 October 2017; "Companies Struggle to Fill Quarter of Skilled Job Vacancies," *Financial Times*, 28 January 2016; "Smaller companies feel the lack of Stem skills most keenly" (*Financial Times*, 16 February 2014).

[29] French labor laws state that mobility between firms within a group cannot be imposed on an employee without her approval. Only the signature of a three-party convention with the explicit approval of the worker – most often in exchange of the transferability of worker's seniority across the firms – makes the transfer possible without it being considered a firing. See `http://www.magazine-decideurs.com/news/la-mobilite-du-salarie-au-sein-d-un-groupe`.

[30]French courts often rely on the ZEMP concept in labor litigations, to establish whether a relocation falls beyond a reasonable distance from the original site of employment. See footnote 19 for a precise definition of ZEMP.

given year.[31] Within each industry, we consider all firms belonging to the same group as a single entity (e.g. summing up their market shares) and estimate the following specification:

$$y_{j(s)t} = \varphi_{j(s)} + \beta_t + \sum_{\tau=-3}^{+3} \alpha_\tau^H I_{\tau j(s)t}^H + \sum_{\tau=-3}^{+3} \alpha_\tau^L I_{\tau j(s)t}^L + \varepsilon_{j(s)t}, \tag{4}$$

where $y_{j(s)t}$ is an outcome observed for firm j at time t. The term $I_{\tau j(s)t}^H$ is a treatment indicator equal to 1 if in year t firm j is τ years away from the event and enjoys high ILM Access. The term $I_{\tau j(s)t}^L$ does the same for firms enjoying low ILM Access. The specification also includes calendar year indicators and firms fixed effects. Given that ILM access (measured at $\tau = -1$) is a time-invariant firm characteristic, its effect at baseline is absorbed by the firm fixed effect. Likewise, given that the identity of the head of the group is fixed at $\tau = -1$, firm fixed effects also control for all time-invariant group characteristics, including size, at $\tau = -1$. As before, standard errors are clustered both by industry, to account for within-industry correlation of the error term across firms of different groups, and by group, to account for within-group correlation of the error term across industries.

In Figure 3 (Table 7) we study how group-affiliated firms' market shares respond to the positive shock, depending on their degree of *ILM Access*. As roughly half of the firms at $\tau = -1$ enjoy no ILM access, we compare the evolution of market shares in this group of (below median) firms to the evolution of market shares in firms whose ILM Access is above the median (panel a), in the top quartile (panel b), top decile (panel c), top 5 percent (panel d) of the distribution.[32]

Figure 3 suggests a strong positive relationship between *ILM Access* and market share growth post event: it is visually evident that the shock has no effect on the market shares of firms with no ILM access, while it has a positive effect on the market shares of high-ILM access firms (statistically different from the effect on below-median ILM access firms). Remarkably, the effect increases with the intensity of ILM access when moving from panel (a) to panel (d) of Figure 3.

The effect is sizeable. For instance, at $\tau = +1$ and $\tau = +2$ firms in the top quartile of the *ILM Access* distribution (panel b) experience an increase in market share of almost 0.3 percentage points, a 21.7% increase with respect to their (pre event) 1.38% share of market sales.[33] Firms in the top decile of the *ILM Access* distribution (panel c) experience an even larger increase in market share of 0.57 percentage points, a 26% increase with respect to their (pre event) 2.2% share of the market.

[31] We remove from the sample stand-alone firms that have have no ILM access by definition, and focus only on comparable group-affiliated firms exploiting the difference in ILM access before the shock for identification purposes. Market-level figures are computed before removing stand-alone firms from the sample.

[32] *ILM Access* for shocked BG firms ranges between 0 and 277,017 workers: the median is equal to 1 worker, the 75th percentile is equal to 35 workers; the 90th percentile is equal to 207 workers, the 95th percentile to 919 workers.

[33] Table A10 in Appendix A.4 reports the pre-event performance of positively shocked firms.

The effect is even more important for firms in the top 5 percent of the *ILM Access* distribution (panel d). For all firms the boost in performance wanes or vanishes at $\tau = +3$.

Figure 4 (Table 8) performs a similar analysis, focusing on financial performance, which we measure with the Return on Assets (ROA). While the results are less clear-cut, they suggest that firms with very high *ILM Access* (panel (d)) translate the market share gains that follows a competitor closure into a financial performance improvement: a 2.2 percentage points increase in Return on Assets at $\tau = +1$ and $\tau = +3$, adding to an average pre-event ROA of 4.67%.

4.2 ILM response and the firm of origin's characteristics

We then investigate in more detail the ILM mechanism. Which group member firms are likely to "provide" more employees to the ones benefiting from a positive shock? Our model suggests that a positively shocked unit should absorb more workers from less productive units and, more generally, from units with less promising prospects. We test this prediction within our event study methodology, comparing internal flows originating from firms with different characteristics. We are able to measure firm-level characteristics such as capital expenditures (Capex) and Value Added Per Worker because we investigate the activity of ILMs within *groups* of affiliated firms, for which separate financial statements are available.

We first ask whether shocked group units absorb more workers from low-productivity units, where we proxy productivity with Value Added Per Worker. Figure 5 (panel (a)) shows that less productive group members contribute more workers to the group ILM after the shock: at $\tau = 0$ and $\tau = 1$, changes in ILM flows from group firms whose (pre-event) Value Added Per Worker is below the median are significantly higher than changes in ILM flows from group firms with (pre-event) Value Added Per Worker above the median (the difference being significant at 1% and at 5% respectively): the latter are not significantly different from zero.[34] In particular, ILM flows from low productivity firms increase by 1.3 percentage points at $\tau = 0$ and by 1.7 percentage points at $\tau = 1$.

We then use pre-event capital expenditures (Capex) as a proxy for growth opportunities. Figure 5 (panel (b)) shows that ILM flows from group units with (pre-event) Capex above the median do *not* react to the shock, while the contribution to the ILM of units with (pre-event) Capex below the median displays a significant and sizeable increase after shock: the fraction of workers absorbed from each low-Capex affiliate increases by 1 percentage point at $\tau = 0$, and by 2, 2.6, and 3 percentage points at $\tau = 1$, $\tau = 2$, $\tau = 3$, respectively (the difference being significant at 5%).[35]

[34] Overlapping confidence intervals are a sufficient, yet not necessary, condition for the difference between two estimated coefficients to be statistically significant.

[35] We also ask whether ILM flows from more levered units (i.e. units whose debt over asset ratio is above the

4.3 ILM response and workers' occupation and age

In this section, we ask whether a positive shock has heterogeneous effects across occupations, to the extent that these may be affected differently by hiring frictions that make the ILM valuable.

We expand equation (3) measuring flows for different categories and estimate the following equation:

$$f_{j(s)kot} = \phi_{j(s)ko} + \beta_t^{Int} + \beta_t^{Ext} + \sum_{o=1}^{4} \sum_{\tau=-3}^{+3} \alpha_{\tau,o}^{Int} I_{\tau st}^{Int} + \sum_{o=1}^{4} \sum_{\tau=-3}^{+3} \alpha_{\tau,o}^{Ext} I_{\tau st}^{Ext} + \varepsilon_{j(s)kot}, \tag{5}$$

where the dependent variable $f_{j(s)kot}$ is the proportion of employees of occupational category o hired by a group affiliated firm j in year t and originating from firm k, relative to the total number of workers hired by firm j in year t. Note that this specification includes fixed effects that are specific to each firm pair and occupation category. This allows us to control for all the unobservable (time-invariant) characteristics that affect bilateral workers flows within a specific occupation category.

In Figure 6 (Table 10) we compare the ILM response across the four main occupational categories in the DADS (see Table A.2): managers, engineers, and professionals; intermediate professions; clerical support, services, and sales workers; blue collars (both skilled and unskilled). We observe a strong ILM response for managerial/high-skill occupations and blue collars. The ILM response is less evident for intermediate professions, while BG firms seem to rely on *both* the external labor market and the ILM to hire clerical workers in response to positive shocks.

Relative to the year before the event, ILM hirings for managers, engineers and professionals significantly increase by 0.34 percentage points at $\tau = +1$ and by 0.44 percentage points at $\tau = +2$ and $\tau = +3$. Given that average internal flows for managers in the pre-event window amount to 2.1% (see Table A9 in Appendix A.4), these increases represent a 16% and 21% boost to ILM flows for this occupational category. ILM hiring of blue collars also registers a similarly sizeable increase (0.39 percentage points at $\tau = 0$, and 0.49 and 0.43 percentage points respectively at $\tau = 1, 2$), which represent about a 20% increase with respect to the pre-event levels (around 2%).[36]

To better understand what drives ILM flows, we analyze results based on a finer classification of occupations, using the technical skill content on top of the position in the firm hierarchy. In Table 11

median) react differently to the closure of a large competitor, when compared to ILM flows from less levered units: our results suggest that the ILM response does *not* depend on the leverage of the firm of origin. Indeed, the effect of financial strength on BG firms' ability to provide or receive workers is far from obvious. Understanding the role of financial strength would call for a richer model allowing for the simultaneous reallocation of labor *and* capital: this is an interesting topic that however lies beyond the scope of our paper.

[36]Note that since we split the total flow of workers within each pair into four occupation categories, the numerator of the dependent variable in equation (5) is smaller than in the baseline specification, hence both average flows and changes in flows are smaller. To grasp the size of the ILM response to positive shocks one has to look at the percentage change in flows.

we report the results for different types of managers and blue-collars (the occupation categories for which reliance on the ILM versus the ELM is stronger).[37] Interestingly, we observe a significant ILM response to competitors' closures in the three years post event for Stem (Science, Technology, Engineering and Maths) skilled managers/professionals, and for skilled blue-collar workers. Conversely, group firms do not increase the ILM hiring of administrative managers/professionals and unskilled blue-collar workers.

Our results suggest that the ILM is particularly valuable in the hiring of skilled/technical workers in both managerial and blue collar positions, which is not surprising given the extensive anecdotal evidence that hiring frictions for these workers are particularly severe (see footnote 28).

To conclude, we also investigate whether the ILM flows after positive shocks vary by worker age (Figure 7 and Table 12). Interestingly, we observe that shocked firms are more prone to absorb older workers from the ILM. Even though we have no data on job tenure, older workers are extremely likely to have a long tenure within the group, reducing informational frictions within the ILM.[38]

5 The ILM Response to Adverse Shocks

In this Section we explore whether groups faced with a negative shock allocate the to-be-displaced workers to other firms within the same group. This will allow us to investigate further the co-insurance role of the internal labor market on the separation side: by alleviating large separation costs for the firm and by avoiding unemployment for the workers. To do so, we exploit episodes of closures and mass layoffs involving group-affiliated firms.

We rely on the episodes of firm closures or mass layoffs identified as described in Section 4.[39] Among those, we focus on all closure events that involve firms affiliated with a group. As we do not include episodes in which a substantial fraction of the lost employment moves to another single specific firm, we do not treat as closures those situations where an affiliated firm (or a large proportion of its workforce) is acquired by another company of the same group. This allows us to minimize concerns about the endogeneity of closures, unless groups selectively close affiliated firms with the aim of finely redeploying their workers to other units. However, to further corroborate that the closure episodes

[37] We split each category in the DADS (see Table A.2) into subgroups. "Managers, engineers and professionals" is divided into: Stem-skilled managers/professionals; administrative managers/professionals; other professionals (legal/arts/entertainment). "Intermediate occupations" into: Stem-skilled versus administration/education/health care. In category 5 we distinguish between clerical workers versus sales/services workers. Finally, blue collars are divided into skilled versus unskilled blue collars. Results for all 10 occupation subgroups are available upon request.

[38] In unreported results (available upon request), we also observe that the ILM activates mainly for male workers.

[39] We regard as closures all episodes in which a firm experiences a drop in employment from one year to the next of 90% or more during our sample period, removing all cases in which more than 70% of the lost employment ends up in a single other firm.

we focus on are genuinely due to adverse shocks, we look at the performance of group-affiliated firms before they close or embark on a mass layoff: Figure 8 shows that sales, return on assets and return on sales all deteriorate in the last two years of activity of the closing firm, denoted as $\tau = -1$ and $\tau = 0$. Interestingly, closing/downsizing group subsidiaries see their coverage ratio (i.e., EBITDA over interest payments) fall below 1 in the last year of activity, which suggests that many closures in our sample are associated with financial default. In sum, we are confident that the closure events we are considering do generate exogenous variation useful in studying the ILM response to negative shocks.[40]

As in Section 4, for each eventually-closing BG firm, we identify the set of all the actual and potential destinations of its workers,[41] and compute the bilateral employment flows (which can be either positive or zero) within each pair of firms in each year, distinguishing again between same-group (ILM) flows, and flows to external labor market (ELM) firms. Our sample consists of 1,894,671 pair-year observations (in which the firm of origin is a BG firm that eventually closes), out of which 59,848 are same-group pairs and 1,834,822 are external labor market pairs (see Table A12 in Appendix A.6). Similar to Section 4, we identify pairs that belong to the same group (or not) based on the group each firm is affiliated at $\tau = -2$, i.e. before the performance decline of the closing firm becomes visible.[42]

Denoting the closure year as the last year of activity of the (eventually) closing firm ($\tau = 0$), we analyze the evolution of ILM and ELM flows originating from the closing firm adopting an event study approach. Our specification is:

$$f_{jkt} = \phi_{jk} + \beta_t^{Int} + \beta_t^{Ext} + \sum_{\tau=-4}^{0} \delta_\tau^{Int} I_{\tau jt}^{Int} + \sum_{\tau=-4}^{0} \delta_\tau^{Ext} I_{\tau jt}^{Ext} + \varepsilon_{jkt}, \tag{6}$$

where f_{jkt} is the ratio of workers moving from BG-affiliated firm j to firm k in year t, to total number of firm-to-firm movers that leave firm j in year t. The treatment indicators $I_{\tau jt}^{Int}$ and $I_{\tau jt}^{Ext}$ equal 1 if year t is τ years away from firm j's closure, for Internal and External flows respectively. Differently from our event study in Section 4, here the event window terminates with the last year of activity of the closing firm. We include firm-pair fixed effects to account for time-invariant pair characteristics (including the group) and year dummies to control for aggregate fluctuations. We cluster standard errors at the (origin) group level, to allow the error term be correlated across firms affiliated with

[40] We also employ a stricter definition of closures, in which we regard as false closures all cases in which 50 percent of the lost employment ends up in a single other firm. Results carry over to this extension (see Table 13).

[41] We consider a labor market partner any firm that in our sample period absorbs at least one employee, in at least one year, from firm i.

[42] Results are robust to fixing the group four years before the closure (see Table 13).

the same group of the closing firm.

The estimated coefficients $\hat{\delta}_\tau^{Int}$ and $\hat{\delta}_\tau^{Ext}$ measure how much the average (internal or external) flows τ years away from closure differ from the counterfactual flows, approximated in equation (6) by the flows outside the $[-4, 0]$ window. Consistently with the choice of fixing the composition of the group two years before the closure, i.e. prior to the sharp decline in the performance of the closing firm, we normalize to zero the coefficient in $\tau = -2$. The difference-in-difference estimate between date -2 and date τ is then calculated as $\widehat{\delta}_\tau - \widehat{\delta}_{-2}$.

Figure 9 plots the estimated normalized coefficients both of the internal flows ($\widehat{\delta}_\tau^{Int} - \widehat{\delta}_{-2}^{Int}$, blue dots) and external flows ($\widehat{\delta}_\tau^{Ext} - \widehat{\delta}_{-2}^{Ext}$, red squares), together with 95% confidence bands. ILM flows steeply increase in the closure year and in the year before, while ELM flows barely change. The fraction of displaced workers redeployed to an ILM firm increases by 12 and 22.6 percentage points at $\tau = -1$ and $\tau = 0$, respectively. Given that average internal flows in the pre-closure window amount to 11% (see Table A13 in Appendix A.6), flows from closing BG firms to ILM partners double at $\tau = -1$ and triple at $\tau = 0$. Importantly, neither ILM nor ELM flows show any pre-existing trend before $\tau = -2$.

Table 13 shows results from the baseline specification – in columns (1) and (2) – and from two robustness checks. Columns (3) and (4) present estimates from an alternative specification in which we fix the group each firm is affiliated with (if any) *and* the reference year at $\tau = -4$.[43] Also in this case, both at closure and in the year before the closure, Internal Labor Market flows increase markedly. ELM flows, instead, while not reacting at closure, show a bit of anticipation as they display a slight increase two and three years before closure. Columns (5) and (6) present results using a stricter definition of the closure events: we label as "false closures" and remove all cases in which at least 50% of the lost employment of the closing firm (rather than 70%) ends up in another single firm. This makes us even more confident that we are ruling out cases where the group selectively closes affiliated firms with the aim of redeploying most of their workers to other units: we obtain results that are similar to the baseline.

We then expand equation (6) and break down the bilateral flows in four different occupation categories, along the lines of Section 4.3.[44] Figure 10 shows that the closure shock has heterogeneous effects across occupational categories. In the closure year and in the year before, ILM activity

[43] This alternative choice reduces the sample size because we lose all the pairs in which one of the two firms is not observed at $\tau = -4$. This is an additional reason to fix the group at $\tau = -2$ and normalize the coefficients accordingly.

[44] More specifically, we measure bilateral flows separately for four occupation categories (blue collars, clerical workers, intermediate professionals and managers) and estimate, in a single specification, all the coefficients relative to the Internal and External flows for each occupational category. As in Equation (5), this specification includes year dummies and firm-pair$\times$occupation fixed effects, to control for all the unobservable time-invariant characteristics that affect the bilateral flows of workers within a specific occupation category.

intensifies substantially for blue-collar workers and, to a smaller extent, for the other occupational categories. At $\tau = -1$ and $\tau = 0$ the estimated ILM coefficient for blue-collar workers is significantly higher than the ILM coefficients estimated for the other categories at a 0.1% level.

More in detail, the fraction of blue-collars (out of total displaced workers) redeployed to an affiliated firm increases by 4.5 percentage points at $\tau = -1$ and by 8 percentage points at $\tau = 0$, a twofold and threefold increase with respect to pre-event ILM flows for this occupational category (which amount to 2.4%: see Table A13 in Appendix A.6). This result suggests that ILMs might be more active, in response to negative shocks, for the occupations for which labor market regulation is stricter. We explore the role of EPL in spurring ILM activity in the next Section.

5.1 Employment protection legislation (EPL) and the ILM

Within the same empirical framework, we investigate the nature of labor market frictions that spur ILM activity. Given the above evidence, labor market regulation is an obvious candidate: we therefore exploit the fact that employment protection in France changes discontinuously at various firm size thresholds. The consensus view is that the 50-employee threshold is critical, a size above which the regulation of employment protection and union rights becomes significantly stricter at various moments of the firm's life, including around closure.[45] Figure 11 shows the distribution of firm size in France: firms bunch just below 50 employees, which suggests that the stricter EPL that applies above 50 employees is likely to matter when firms make decisions. Previous work has studied the distortions that this type of legislation creates by discouraging firms' expansion.[46]

We adopt a regression discontinuity-like approach and focus on firms between 40 and 60 employees (Appendix Table A15 shows that covariates are balanced around the 50-employee threshold). Then, we run an event study distinguishing firms above the 50-employee threshold at closure and firms below the 50-employee threshold at closure:

$$\begin{aligned} f_{jkt} &= \phi_{jk} + \beta_t^{Int} + \beta_t^{Ext} + \sum_{\tau=-4}^{0} \delta_\tau^{Int,B50} I_{\tau jt}^{Int,B50} + \sum_{\tau=-4}^{0} \delta_\tau^{Ext,B50} I_{\tau jt}^{Ext,B50} \\ &\quad + \sum_{\tau=-4}^{0} \delta_\tau^{Int,A50} I_{\tau jt}^{Int,A50} + \sum_{\tau=-4}^{0} \delta_\tau^{Ext,A50} I_{\tau jt}^{Ext,A50} + \varepsilon_{jkt}, \end{aligned} \tag{7}$$

[45] In case of collective dismissals (i.e. dismissals of at least 10 workers during a 30 days period), firms with 50+ employees are required to formulate an "employment preservation plan" in close negotiation with union representatives. The aim of the plan is to lay out solutions to facilitate reemployment of terminated workers. In practice, the obligations entailed by the plan substantially increase termination costs (by raising both lay-off costs and union bargaining power). The "employment preservation plan" must be formulated also in the event of a closure. See Appendix A.7.

[46] In their study of the impact of size-contingent labor laws, Garicano, Lelarge, and Van Reenen (2016) focus precisely on the French 50-employee threshold.

As internal and external flows as well as flows above and below the threshold are now subject to treatment, equation (7) includes separate treatment indicators for internal and external flows below the threshold, namely $I_{\tau jt}^{Int,B50}$ and $I_{\tau jt}^{Ext,B50}$, and for internal and external flows above the threshold, namely $I_{\tau jt}^{Int,A50}$ and $I_{\tau jt}^{Ext,A50}$. As before, we allow for different cyclicality of internal and external flows adding separate sets of calendar year dummies β_t^{Int} and β_t^{Ext} and control for the time-invariant unobservable characteristics of the pair of firms (including the group they are affiliated with) through the firm-pair fixed effect term ϕ_{jk}.

In our baseline specification we allocate firms above and below the threshold based on the number of employees at closure ($\tau = 0$). However, to achieve proper identification this approach requires firms to be randomly allocated above and below the 50-employee threshold. The use of firm pair fixed effects already controls for all the time-invariant unobserved factors that may affect the propensity of firms to self-select into (or out of) treatment; yet, fixed effects do not account for selection due to time-varying factors. Therefore, to (at least partially) account for the possibility that firms, at closure, self-select above/below the threshold, we also estimate a second specification where we assign firms to treatment using firm size at $\tau = -2$, when the firm performance has not fully deteriorated yet.

Figure 12 shows results, measuring firm size at $\tau = 0$ (left panel) and $\tau = -2$ (right panel). In both panels, stricter EPL does seem to matter as, at event date $\tau = -1$, ILM outflows increase significantly more in closing firms with more than 50 employees than in closing firms with less than 50 employees. Since all the coefficients are estimated within the equation (7), we are able to formally test the significance of the difference between the ILM response of firms subject to a strict versus a soft EPL regime. At $\tau = -1$ the difference is positive and significant both in our baseline specification (with a p-value of 0.006) and in the alternative specification that relies on firm size at $\tau = -2$ (with a p-value of 0.036). No significant difference appears at $\tau = 0$. These results suggests that group-affiliated firms hit by adverse shocks are more prone to rely on the ILM when they are subject to more stringent employment protection rules, at least one year prior to closure. Interestingly, both in the closure year and in the year before, ILM flows increase even from closing firms with less than 50 employees. The reason might be that in France employment protection legislation is lighter but non negligible also for firms below 50; additionally, we cannot exclude that other frictions beyond EPL contribute to ILM activity.[47]

We obtain similar results when restricting the analysis to firms between 45 and 55 employees

[47] For instance, asymmetric information and search costs may induce the group to keep valuable workers within its perimeter by relocating them to other firms.

(reported in columns (5)-(8) of Table 15): ILM flows increase in the closure year and in the year before both in firms above and below 50 employees, with a significantly larger increase at $\tau = -1$ for closing firms with more than 50 employees. The difference between coefficients is positive and 10% significant ($p = 0.086$) in our baseline specification (columns (5)-(6)), and 5% significant ($p = 0.048$) in the alternative specification of columns (7)-(8) which relies on firm size at $\tau = -2$. When we restrict the analysis to firms between 35 and 65 employees, the ILM response is significantly larger at $\tau = -1$ for closing firms with more than 50 employees compared to closing firms below 50 employees ($p = 0.019$) in the baseline specification (columns (9)-(10)); however the difference in the estimated coefficients decreases in the specification that relies on size at $\tau = -2$ (columns (11)-(12)) and, while still positive, loses significance.

5.2 Employment flows at closure: Where do workers go?

This section investigates the characteristics of the firms that absorb a closure event (our negative shock) by hiring the workers displaced from the closing firms. We measure the average characteristics of the destination firms between $\tau = -4$ and $\tau = -2$, i.e. before they are possibly affected by the firm of origin's closure. This addresses the concern that a firm's closure is likely to affect the productivity and investment policy of both its external and ILM destination firms. If groups run ILMs efficiently, one would expect them to reallocate displaced employees to firms that would benefit from absorbing the workforce of closing units, i.e. more productive firms with profitable growth opportunities.[48]

Figure 13 (panel (a)) shows that at $\tau = -1$ flows to ILM firms whose Value Added Per Worker is higher than the median are 5 percentage points higher than flows to ILM firms with lower-than-median VA Per Worker (the difference is significant at 0.1%), while no significant difference appears at $\tau = 0$. These results suggest that closing BG firms redeploy workers mostly to their more productive group affiliates, at least in the year prior to the closure.

We then ask whether group ILMs reallocate displaced workers more intensely towards group affiliates that enjoy more growth opportunities, which (as in Section 4) we proxy with average pre-event capital expenditures (Capex). Figure 13 (panel (b)) shows that at $\tau = -1$ group subsidiaries that have been investing more in the years prior to a closure event absorb more displaced workers (the 6 percentage points difference is significant at 0.1%), while we do not find any difference in flows

[48] A related albeit different question is whether the ILM redeploys employees more or less intensely towards subsidiaries that are directly controlled by the parent as opposed to indirectly controlled subsidiaries in pyramidal groups (we thank Bill O'Brien for raising this issue). Unfortunately, the LIFI dataset only provides information on whether firms are controlled by a common ultimate owner (whether directly or indirectly), and thus are part of the same group. Hence, our data do not allow us to explore the relationship between the ILM and the precise hierarchical structure of each group.

at $\tau = 0$.

This result complements the findings of Tate and Yang (2015), who study the change in sectoral Tobin's Q growth experienced by workers who switch industry after a plant closure. They find that workers who move across establishments in the same firm experience a higher change in sectoral Tobin's Q growth, as compared to workers who move outside the firm. We add to their evidence by investigating the size of ILM flows and showing that the proportion of displaced workers who are reallocated internally increases if the destination firm is on an expansion trajectory.[49,50] More importantly, our paper shows that ILMs do not just have value in bad times, when a workforce reduction is called for; indeed, we show that the ILM allows groups to better take advantage of expansion opportunities.

5.3 Employment insurance provided by the ILM

Our finding that closing group units extensively redeploy labor through the internal labor market suggests that workers employed in group-affiliated firms are provided with implicit employment insurance against adverse shocks hitting their company. To corroborate this hypothesis, we study whether, in the run-up to a closure, fewer employees of group-affiliated firms become unemployed as compared with those employed in stand-alone firms. We therefore implement an event study to analyze how the number of workers moving to unemployment (normalized by the size of the firm's workforce) evolves around a closure/mass layoff, in stand-alone versus group-affiliated firms.

$$u_{jt} = \varphi_j + \beta_t + \sum_{\tau=-4}^{0} \alpha_\tau^{BG} I_{\tau jt}^{BG} + \sum_{\tau=-4}^{0} \alpha_\tau^{SA} I_{\tau jt}^{SA} + \varepsilon_{jt}, \tag{8}$$

where u_{jt} is the fraction of workers moving to unemployment from firm j at time t divided by the employment stock of firm j at $\tau = -2$. The term $I_{\tau jt}^{BG}$ is a treatment indicator equal to 1 in year t if the BG-affiliated firm j is τ years away from the event. The term $I_{\tau jt}^{SA}$ does the same for stand-alone firms. The specification also includes calendar year dummies and firms fixed effects. Given that the identity of the head of the group is fixed at $\tau = -2$, the firm fixed effect also controls for all time-invariant group characteristics. As before, standard errors are clustered by group to account for within-group correlation of the error term.

Figure 14 (and associated Table 17) shows that flows to unemployment increase significantly in

[49] Additionally, the richness of our data allows us to do so exploiting only the within-pair time variation, thus controlling for any unobserved heterogeneity across pairs of firms.

[50] Tate and Yang (2015) also find that workers displaced from closing plants of a diversified firm are more likely to be retained inside the firm the larger the average Tobin's Q in the other industries where the firm operates. This result shows that internal reallocation occurs within firms but is silent on whether the retained workers actually move towards the plants operating in more promising industries.

the closure year and in the previous year for all closing firms, but stand-alone firm workers experience a significantly larger exposure to unemployment than BG workers. The year before closure (i.e. at $\tau = -1$) the proportion of workers who become unemployed increases almost twice as much in stand-alone firms than in BG firms: an increase of 8.3 versus 4.7 percentage points in the fraction of the firm's workforce that becomes unemployed (the difference being significant at 0.1%). In the last year of activity of the closing firms ($\tau = 0$), the proportion of workers who become unemployed increases by 5.1 percentage points in stand alone firms versus 4.3 in BG firms but the difference is not statistically significant.

In Figure 15 (and Table 18) we investigate whether this effect differs across occupational categories. Results suggest that blue collar workers and clerical workers benefit from business groups' employment insurance: both at $\tau = -1$ and $\tau = 0$ the difference between the coefficient of unemployment flows from stand-alone firms and the one of unemployment flows from affiliated firms is positive and significant for both categories of workers.[51]. For intermediate professionals, flows from stand-alone firms are not significantly different than flows from affiliated firms. Finally, BG managers seem to be more exposed to unemployment risk than stand-alone managers, at least at $\tau = 0$. Hence, ILMs appear to allow groups to provide employment insurance in the face of negative shocks to those employees with fewer outside options and, possibly, protected by stronger EPL.[52]

We then ask whether BG employees pay a price *ex-post* for the preservation of their employment within their group, when their firm experiences an adverse shock.[53] To answer this question, one would ideally exploit a panel of workers and compare the stream of wages of displaced workers that find a job in another affiliate of their group with the stream of wages of displaced workers that find a job in the external labor market. Unfortunately (as explained in section 3.1) the DADS Postes,

[51] The difference in the coefficients estimated for blue collar workers is significant at 0.1% at $\tau = -1$ and at 5% at $\tau = 0$. For clerical workers, the difference is significant at 0.1% at $\tau = -1$ and at 1% at $\tau = 0$.

[52] Finding that, conditional on their firm being subject to a closure, BG workers are less likely to go to unemployment does not *per se* imply that BG workers enjoy more job stability than stand-alone firm workers: this would not necessarily be the case if BG employers were more likely to shut down than stand-alones. Table A17 in the Appendix shows that BG firms are, if anything, slightly less likely to experience closures: this makes us confident that our results do support the claim that employment in a BG firm is safer than employment in a stand-alone. Furthermore, this result implies that the ILM effect we estimate is the response to adverse shocks that are severe enough to trigger a BG firm closure. Indeed, our model predicts that with linear firing costs, reliance on the ILM (the fraction of displaced workers redeployed through the ILM) is weakly decreasing in the severity of the shock (this is because when facing small shocks it is more likely that the firm is able to fully adjust using the less frictional ILM). This in turn suggests that we are possibly *underestimating* the extent to which labor adjustments are performed through the ILM after an adverse shock, i.e. our estimates are, if anything, a lower bound. We thank an anonymous Referee for raising these issues.

[53] Another important question is whether BG workers pay an employment insurance premium *ex ante*, by accepting lower wages (in expected present discounted value) with respect to stand-alone firm workers. To investigate this issue, in particular using the event study methodology, one would ideally compare the wage evolution of two identical workers both displaced, hired in otherwise identical stand-alone and BG-affiliated firms. This strategy requires the availability of a full panel of worker and firms, not only to be able to reconstruct the employment history of the workers but also, thanks to the panel structure, to account for selection and unobserved heterogeneity at the worker and firm level. As the DADS Postes is not a full fledged panel of workers, we are forced to leave this issue for future research.

the version of the DADS we work with, is not a full-fledged panel of workers: this only allows us to assess the short-run wage effect, as we can only observe the wage in the first year after displacement.

Table 19 shows the results of this analysis: it examines the change in hours worked (columns 1 and 2), in the hourly wage (columns 3 and 4) and in the annual wage (columns 5 and 6), for workers transiting from closing firm j to firm k at time t (the unit of observation is now the worker). The coefficient of *Closure* $\times$ *Same Group* indicates that closures have a more detrimental effect on hours worked and on the annual wage for employees redeployed to an ILM destination firm, as compared to employees that find a new job in the external labor market (with no differential impact across different occupational categories). Instead, closures have no differential impact on the *hourly* wage.[54] These results suggest that the higher job stability granted by the group does come at a cost: when a BG worker is redeployed internally, her hours worked are reduced and so is her annual wage

6 Conclusion

Why are some organizations more resilient to shocks than others? Which channels allow them to swiftly respond to adverse or favorable economic conditions? In this paper we address these questions by studying how some widespread organizations, namely business groups, cope with shocks using their Internal Labor Markets. To this end, we exploit measures of individual mobility (through a matched employer-employee data set), together with information on the organization's structure (i.e., the firms affiliated with a group), and the economic outcomes of the affiliated firms.

To the best of our knowledge, ours is the first paper to show that labor market regulations and hiring frictions in the external labor market induce organizations to use internal labor markets when responding to both adverse and positive shocks. It is also the first to show that access to human capital through the internal labor market boosts performance in the aftermath of positive shocks to growth opportunities. Our evidence suggests that ILMs emerge as a mutual insurance mechanism across firms of diversified groups in the presence of frictions. As a by-product of ILM activity, implicit employment insurance is provided to the organizations' workers, in particular the low-skilled.

Our findings are in line with the idea that participation in a business network may iron information frictions and boost firm performance (see Cai and Szeidl (2018)). However, they raise several issues regarding the wider role of business group organizations in economic systems. The evidence provided here suggests that, in the presence of frictions, groups display a higher ability to adapt to changing

[54]Managers seem to enjoy an hourly wage premium when moving within the group (*Same Group* $\times$ *Managers* in column 3), almost completely dissipated upon closure (*Same Group* $\times$ *Closure* $\times$ *Managers*). These effects vanish in column (4) in which we control for the pair fixed effect, suggesting that the wage premium in normal times is due to the managers (self) selecting into high-wage firms.

business conditions with respect to stand-alone firms: thanks to the ILM, groups can swiftly downsize business units hit by adverse shocks, but also overcome human capital bottlenecks that may bind when growth opportunities emerge. Hence, ILMs, alongside internal capital markets, can provide groups with a competitive advantage with respect to their stand-alone rivals, an imbalance that labor market frictions are bound to magnify.[55]

A second question is how group ILMs alter the allocation of labor in the economy. On the one hand, ILMs ensure the reallocation of workers to more productive uses in situations where stand-alone companies would inefficiently hoard labor to avoid adjustment costs; on the other hand, the ability of groups to rely on the ILM, while privately beneficial in the presence of frictions, may prevent more efficient matches to emerge in the external labor market. The above considerations imply that groups have multiple and complex effects on competition, factor allocation, and the efficiency of economic systems; assessing whether economies benefit from the presence of groups is an important goal that however lies beyond the scope of this paper (see Almeida and Wolfenzon (2006)).[56]

Our results are likely to extend beyond the group-type organizational form. Indeed, ILMs are even more likely to operate within other types of diversified organizations such as multi-establishment firms, where coordination across units is arguably stronger than across subsidiaries of a business group.[57] Focusing on groups is a useful benchmark because it allows us to establish that ILMs operate even across units that are separate legal entities, as is the case for business group subsidiaries.[58]

Because taking the structure of these complex organizations as given is far from fully satisfactory, our next steps will aim at understanding how such entities come to life and why they take different forms. Why are some units added to these organizations as separate legal entities under the parent control rather than as establishments? In order to understand the full nature of the benefits and costs associated to groups' existence, we will in particular focus on how shocks lead to the addition of new firms within groups versus new establishments in multi-establishment firms. We have started to examine how large exchange-rate movements with the potential to affect the location of businesses

[55]Our data show that groups enjoy strong positions in their product markets: 89 percent of the ten largest incumbents in French manufacturing industries are affiliated with business groups. In a previous paper, three of the four co-authors studied how reliance on internal capital markets can explain groups' ability to withstand competition, especially in environments where financial constraints are pronounced (Boutin, Cestone, Fumagalli, Pica, and Serrano-Velarde (2013)).

[56]Almeida and Wolfenzon (2006) point out that business groups' internal *capital* markets negatively affect the efficiency of the economy-wide capital allocation. In their model, even if conglomerates run internal capital markets efficiently, they exert a negative externality on the economy by reducing the supply of capital to other firms, thus lessening allocative efficiency.

[57]Resource reallocation within multi-establishment firms has been the focus of much of the literature on internal markets. Recently, this has raised the question of whether firms' internal networks of establishments may contribute to propagate local economic shocks across regions (see Giroud and Mueller (2017)).

[58]Measurement is a further reason for studying complex organizations in the shape of groups comprising multiple firms rather than firms comprising multiple establishments: indeed, unlike for establishments, one can measure debt, earnings, sales and capital expenditure for each separate group subsidiary .

impact these two organizational forms. Contrasting the reactions of different organizations when faced with the changing environments induced by such exchange-rate movements – reactions measured by imports, exports, purchases within France, firms' creation or destruction – we will try to assess the benefits and limits of integration.

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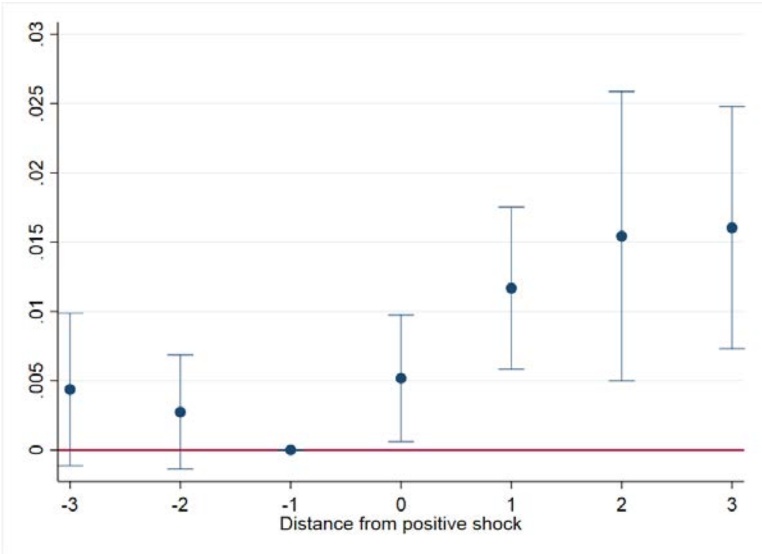
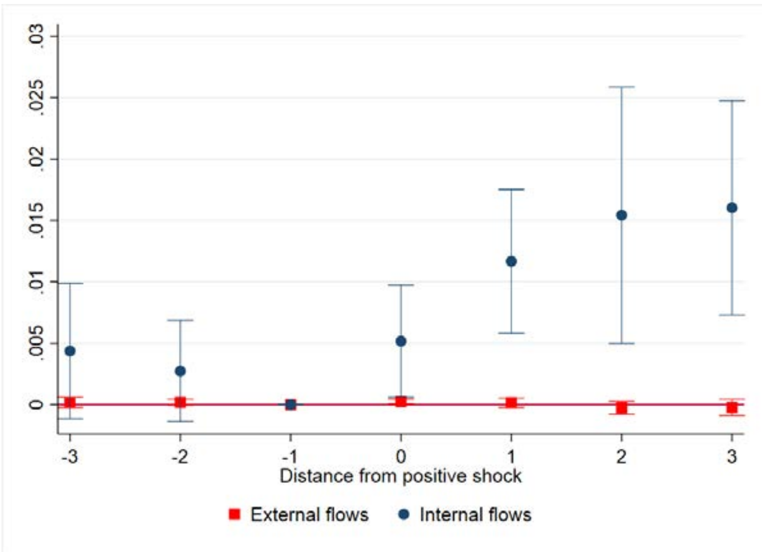
Figure 1: Impact of competitors' closures on worker flows



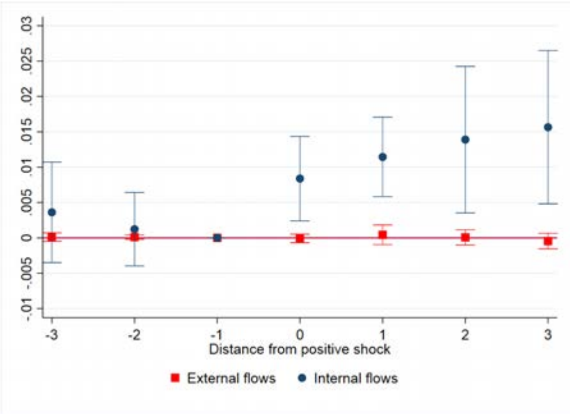
(a) ILM pairs



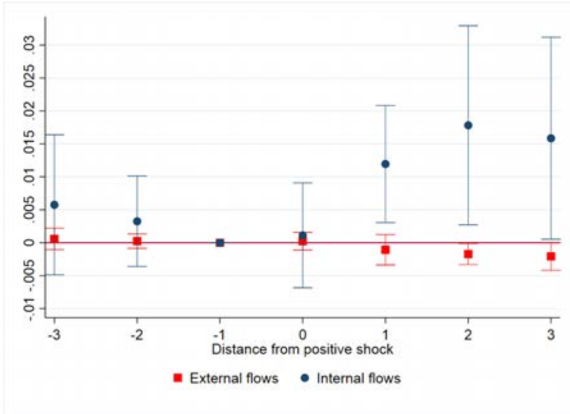
(b) ILM and ELM pairs

Note: Panel (a) plots the coefficients $\widehat{\alpha}_{\tau}^{Int} - \widehat{\alpha}_{-1}^{Int}$ estimated from equation 2. Panel (b) plots the coefficients $\widehat{\alpha}_{\tau}^{Int} - \widehat{\alpha}_{-1}^{Int}$ (blue dots) and $\widehat{\alpha}_{\tau}^{Ext} - \widehat{\alpha}_{-1}^{Ext}$ (red squares) jointly estimated from equation 3. The coefficients measure the change in Internal and External flows from event date -1 to event dates $\tau \in [-3, +3]$ (relative to the counterfactual flows). Event date 0 is the year of the positive shock, i.e. the first year in which the large competitor is no longer active in a given industry. The error bars show the 95% confidence intervals calculated using standard errors that are clustered at the industry and group level. We include firm-pair fixed effects and year dummies in our specification. The flows are measured as the ratio of workers hired by a BG-affiliated firm j (active in a shocked industry) from firm k in year t, to the total number of workers hired by firm j in year t. Table 5 reports the estimated coefficients, standard errors and sample size.

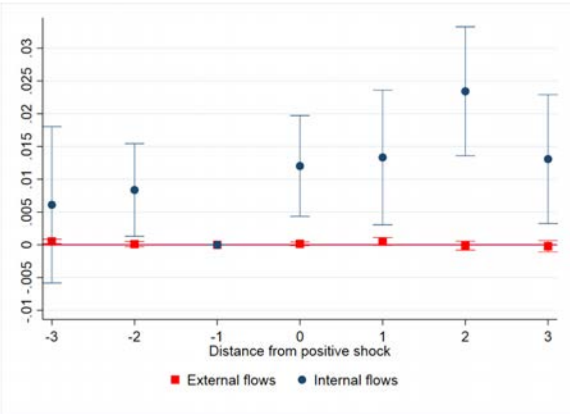
Figure 2: Impact of competitors' closures on ILM and ELM flows from firms operating in same/different industry or local labor market



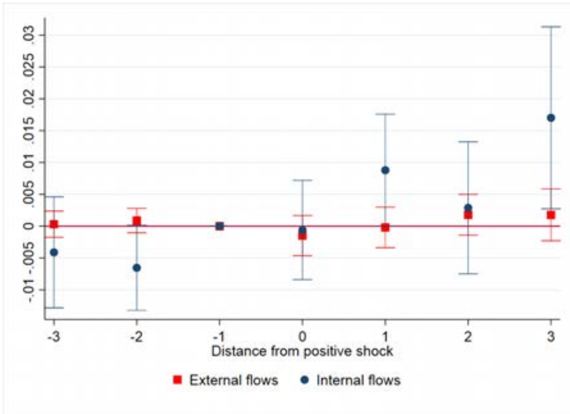
(a) Flows from firms in different local labor market



(b) Flows from firms in same local labor market



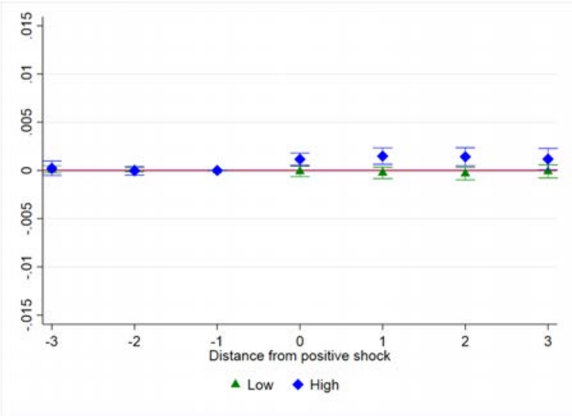
(c) Flows from firms in different 4 digit industries



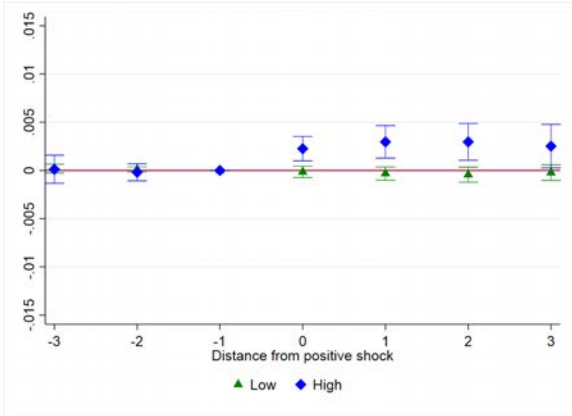
(d) Flows from firms in same 4 digit industry

Note: Panels (a) and (b) of the figure plot the coefficients $\widehat{\alpha}^{Int}_{\tau} - \widehat{\alpha}^{Int}_{-1}$ (blue dots) and $\widehat{\alpha}^{Ext}_{\tau} - \widehat{\alpha}^{Ext}_{-1}$ (red squares) estimated in a single specification in which we distinguish flows within pairs where the firm of origin operates in a different local labor market than firm j (estimates displayed in panel (a)) and flows within pairs where the firm of origin operates in the same local labor market as firm j (estimates displayed in panel (b)). Panels (c) and (d) plot the coefficients estimated in a single specification in which we distinguish flows within pairs where the firm of origin operates in a different 4 digit industry than firm j (estimates displayed panel (c)) and the same 4 digit industry as firm j (estimates displayed panel (d)). The plotted coefficients measure the change in Internal and External flows from event date -1 to event dates $\tau \in [-3, +3]$ (relative to the counterfactual flows). Event date 0 is the year of the positive shock, i.e. the first year in which the large competitor is no longer active in a given industry. The error bars show the 95% confidence intervals calculated using standard errors that are clustered at the industry and group level. We include firm-pair fixed effects and year dummies in our specification. The flows are measured as the ratio of workers hired by a BG-affiliated firm j (active in a shocked industry) from firm k in year t, to the total number of workers hired by firm j in year t. Table 6 reports the estimated coefficients, standard errors and sample size.

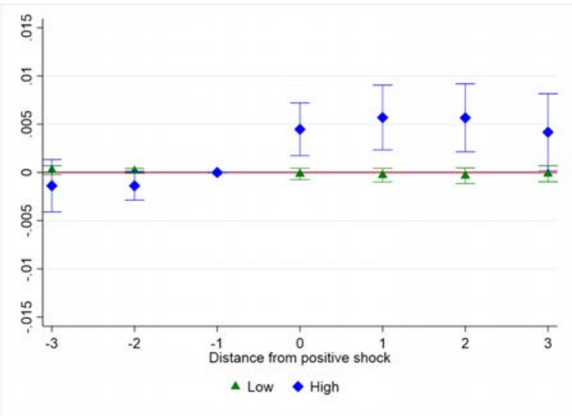
Figure 3: Impact of competitors' closures on BG firms' market share, by *ILM Access*



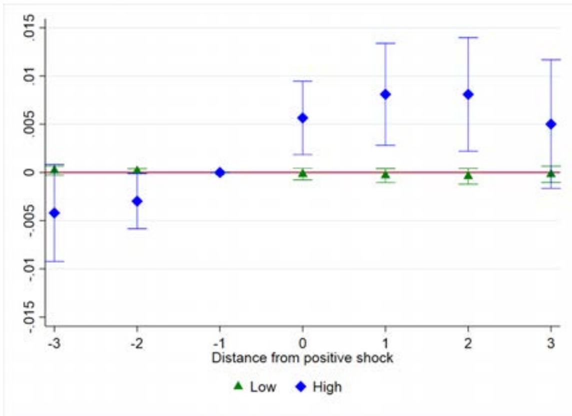
(a) ILM Access above median vs. below median



(b) ILM Access in top quartile vs. below median



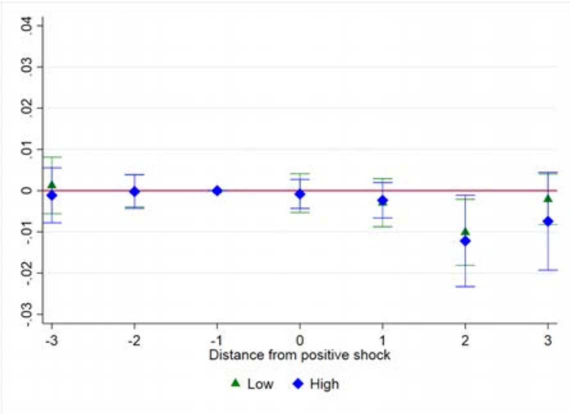
(c) ILM Access in top decile vs. below median



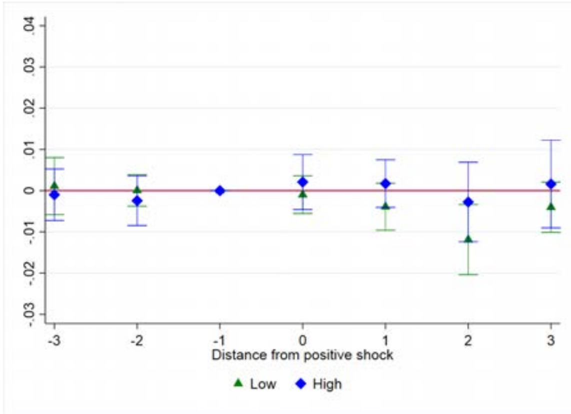
(d) ILM Access in top 5 percent vs. below median

Note: The figure shows the effect of a large competitor closure on shocked BG firms' market share, depending on the level of *ILM Access* (see equation 4). *ILM Access* is the sum of employment (measured at $\tau = -1$) of all group units that are (i) affiliated with firm j; (ii) located in the same local labor market (*Zone d'Emploi*) as firm j; (iii) in a different 4-digit industry than j. Event date 0 is the year of the positive shock, i.e. the first year in which the large competitor is no longer active in a given industry. The blue diamonds plot the change in market share from event date -1 to event dates $\tau \in [-3, +3]$ (relative to the counterfactual flows) for firms with *ILM Access* above the median (panel a); in the top quartile (panel b); top decile (panel c); top 5 percent (panel d) of the distribution. The green triangles represent the change in market share for firms with below median *ILM Access*. The median value of *ILM Acces* is equal to 1 worker, the 75th percentile is equal to 35 workers; the 90th percentile is equal to 207 workers, the 95th percentile to 919 workers. The error bars show the 95% confidence intervals calculated using standard errors that are clustered at the industry and group level. We include firm fixed effects and year dummies in our specification. Table 7 reports the estimated coefficients, standard errors and sample size.

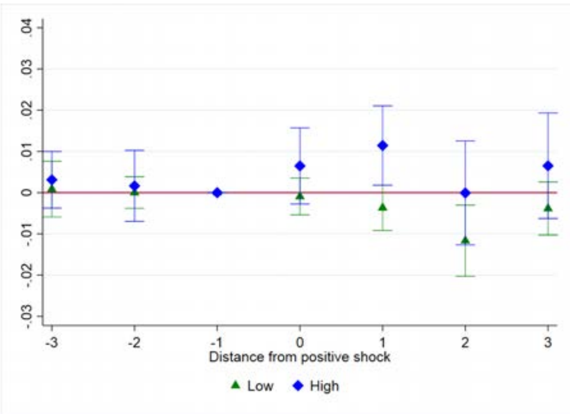
Figure 4: Impact of competitors' closures on BG firms' Return on Assets, by *ILM Access*



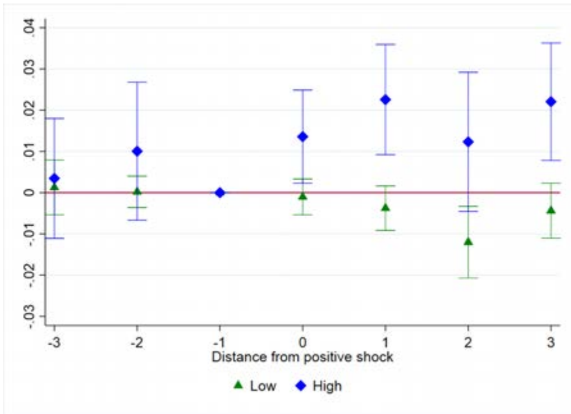
(a) ILM Access above median



(b) ILM Access in top quartile



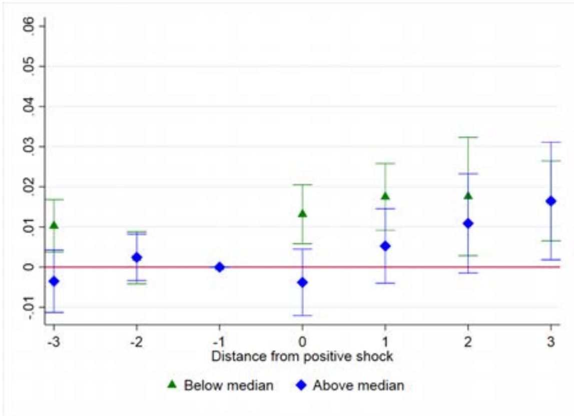
(c) ILM Access in top decile



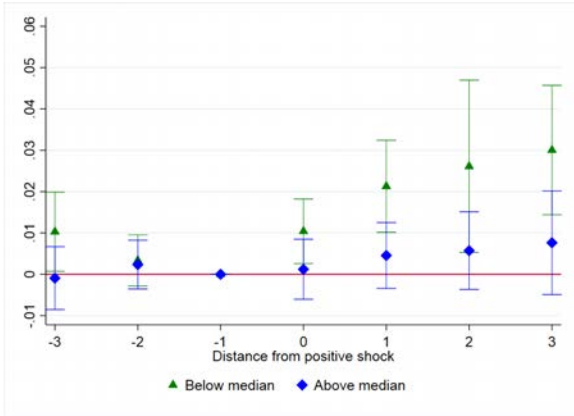
(d) ILM Access in top 5 percent

Note: The figure shows the effect of a large competitor closure on shocked BG firms' Return on Assets (ROA), depending on the level of *ILM Access* (see equation 4). ROA is defined as EBITDA over Total Assets. *ILM Access* is the sum of employment (measured at $\tau = -1$) of all group units that are (i) affiliated with firm j; (ii) located in the same local labor market (*Zone d'Emploi*) as firm j; (iii) in a different 4-digit industry than j. Event date 0 is the year of the positive shock, i.e. the first year in which the large competitor is no longer active in a given industry. The blue diamonds plot the change in ROA from event date -1 to event dates $\tau \in [-3, +3]$ (relative to the counterfactual flows) for firms with *ILM Access* above the median (panel a); in the top quartile (panel b); top decile (panel c); top 5 percent (panel d) of the distribution. The green triangles represent the change in ROA for firms with below median *ILM Access*. The median value of *ILM Acces* is equal to 1 worker, the 75th percentile is equal to 35 workers; the 90th percentile is equal to 207 workers, the 95th percentile to 919 workers. The error bars show the 95% confidence intervals calculated using standard errors that are clustered at the industry and group level. We include firm fixed effects and year dummies in our specification. Table 8 reports the estimated coefficients, standard errors and sample size.

Figure 5: Impact of competitors' closures on ILM flows, by firm of origin characteristics



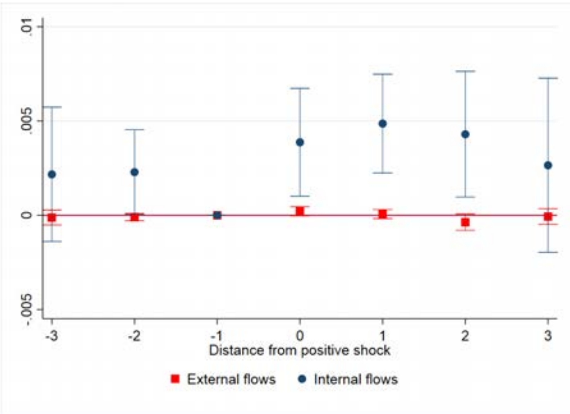
(a) Flows from firms with high vs low pre-event Value Added Per Worker



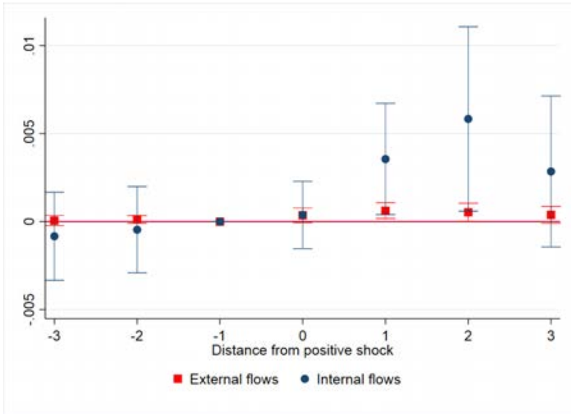
(b) Flows from firms with high vs low pre-event Capex

Note: The figure shows the effect of a large competitor closure on bilateral worker flows from ILM partners to shocked BG firms. All firm of origin characteristics are measured as pre-event averages, taking the average over the pre-treatment period within the event window, i.e. over years $\tau \in [-3, 0)$. In panel (a), we compare flows from same-group firms with (average pre-event) Value Added Per Worker above versus below the median. At $\tau = 0$ and $\tau = 1$ ILM flows from firms with low VA per Worker are significantly higher than ILM flows from firms with high VA per Worker; the difference being 1% significant at $\tau = 0$ ($p = 0.0075$) and 5% significant at $\tau = 1$ ($p = 0.03$). In panel (b), we compare flows from same-group firms that have average pre-event Capex above versus below the median of the Capex distribution. ILM flows from low Capex firms are significantly higher than ILM flows from high Capex firms: the difference is significant at 5% at $\tau = 1$ ($p = 0.017$), $\tau = 2$ ($p = 0.044$), and $\tau = 3$ ($p = 0.025$). The flows are measured as the ratio of workers hired by a BG-affiliated firm j (active in a shocked industry) from firm k in year t, to the total number of workers hired by firm j in year t. Event date 0 is the year of the positive shock, i.e. the first year in which the large competitor is no longer active in a given industry. The plotted coefficients measure the change in bilateral worker flows from event date -1 to event dates $\tau \in [-3, +3]$, relative to the counterfactual flows. The error bars show the 95% confidence intervals calculated using standard errors that are clustered at the industry and group level. We include firm-pair fixed effects and year dummies in our specification. Table 9 reports the estimated coefficients, standard errors and sample size.

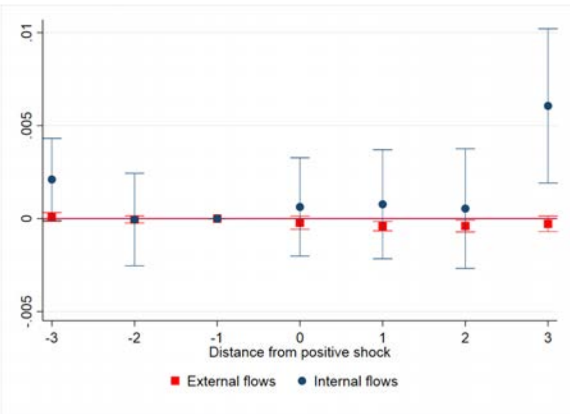
Figure 6: Impact of competitors' closures on ILM and ELM flows, by occupation



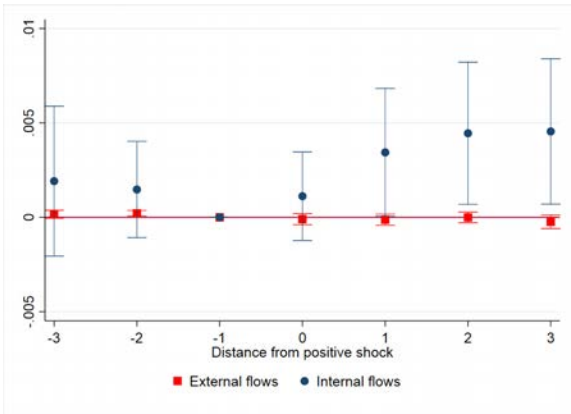
(a) Blue Collars



(b) Clerical Workers



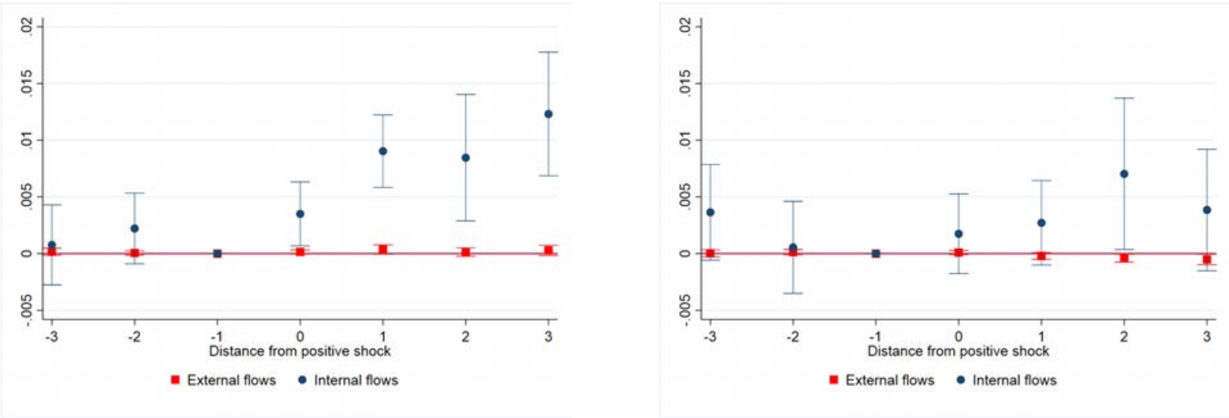
(c) Intermediate Professions



(d) Managers/High-skill

Note: The figure plots the coefficients $\widehat{\alpha}^{Int}_{\tau} - \widehat{\alpha}^{Int}_{-1}$ (blue dots) and $\widehat{\alpha}^{Ext}_{\tau} - \widehat{\alpha}^{Ext}_{-1}$ (red squares) estimated from equation 5. We consider for four occupational categories: blue collars, clerical workers, intermediate professions, managers/high-skill workers. Event date 0 is the year of the positive shock, i.e. the first year in which the large competitor is no longer active in a given industry. The flows are measured as the ratio of workers *in a given occupational category* hired by a BG-affiliated firm j (active in a shocked industry) from firm k in year t, to the total number of workers hired by firm j in year t. The plotted coefficient measure the change in Internal and External flows from event date -1 to event dates $\tau \in [-3, +3]$ (relative to the counterfactual flows). The error bars show the 95% confidence intervals calculated using standard errors that are clustered at the industry and group level. We include firm-pair$\times$occupation fixed effects and year dummies in our specification. Table 10 reports the estimated coefficients, standard errors and sample size.

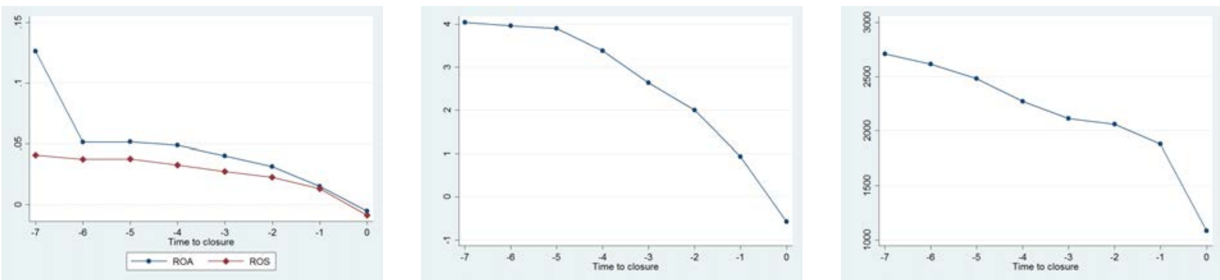
Figure 7: Impact of competitors' closures on ILM flows, by worker age



(a) Old (b) Young

Note: The figure displays the estimated coefficients $\widehat{\alpha}_{\tau}^{Int} - \widehat{\alpha}_{-1}^{Int}$ (blue dots) and $\widehat{\alpha}_{\tau}^{Ext} - \widehat{\alpha}_{-1}^{Ext}$ (red squares) estimated in a specification in which we distinguish flows of workers under 40 years of age (panel (b)) and flows of workers over 40 years of age (panel (a)). Event date 0 is the year of the positive shock, i.e. the first year in which the large competitor is no longer active in a given industry. The plotted coefficients measure the change in Internal and External flows from event date -1 to event dates $\tau \in [-3, +3]$ (relative to the counterfactual flows). The flows are measured as the ratio of workers *in a given age category* hired by a BG-affiliated firm j (active in a shocked industry) from firm k in year t, to the total number of workers hired by firm j in year t. The error bars show the 95% confidence intervals calculated using standard errors that are clustered at the industry and group level. We include firm-pair $\times$ age group fixed effects and year dummies in our specification. Table 12 reports reports the estimated coefficients, standard errors and sample size.

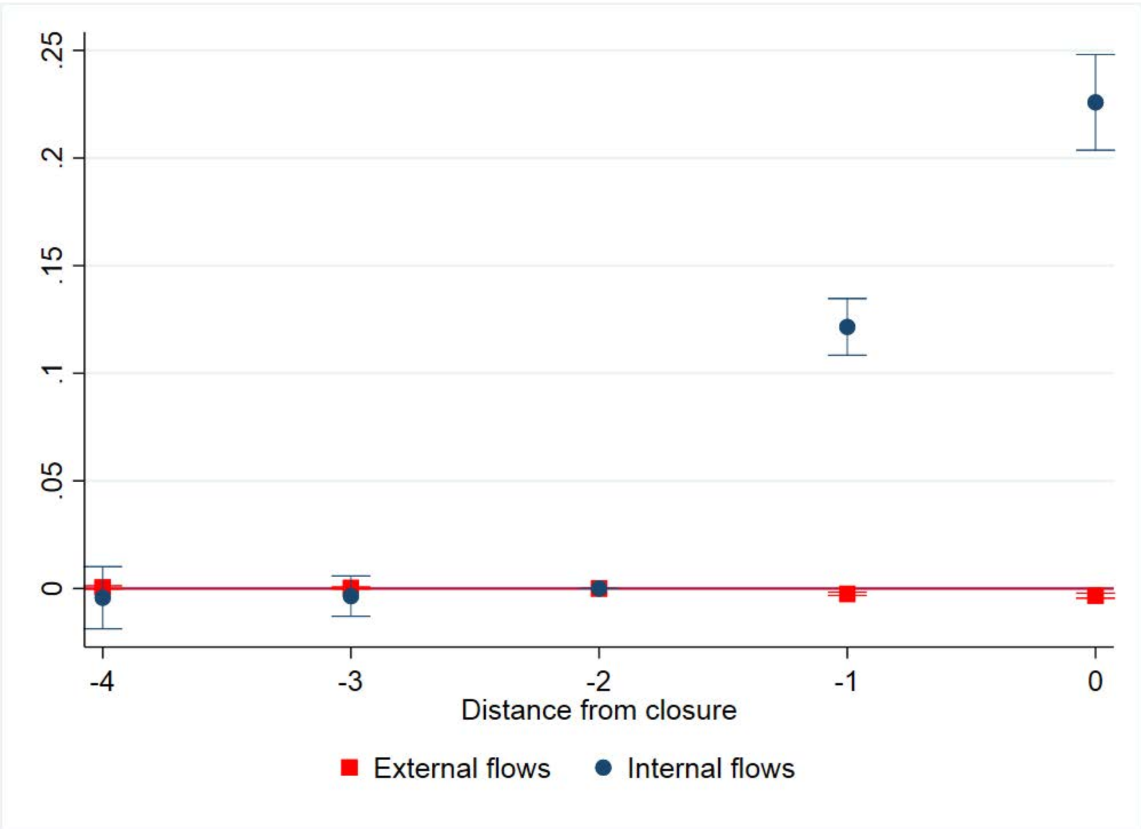
Figure 8: Evolution of performance indicators for group affiliated closing firms



(a) ROA and ROS (b) Interest Coverage Ratio (c) Sales

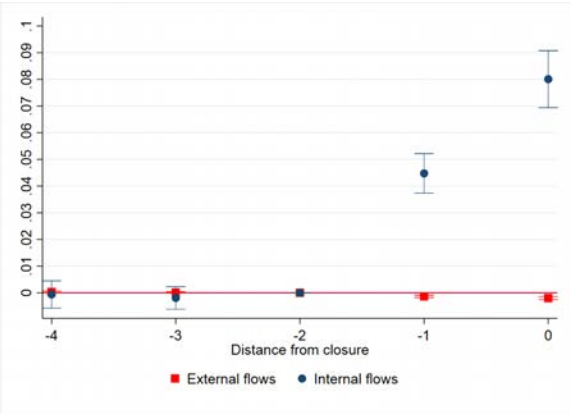
Note: ROA denotes median return on assets (EBITDA over Total Assets); ROS denotes median return on sales (EBITDA over Total Sales); interest coverage is the median ratio of EBITDA over interest payments. (Median) Sales are measured in thousands of Euros. 0 denotes the last year of activity of the closing firm, i.e. the closure year. Time to closure indicates the number of years before the closure event.

Figure 9: Impact of firm closures on worker flows towards ILM and ELM firms

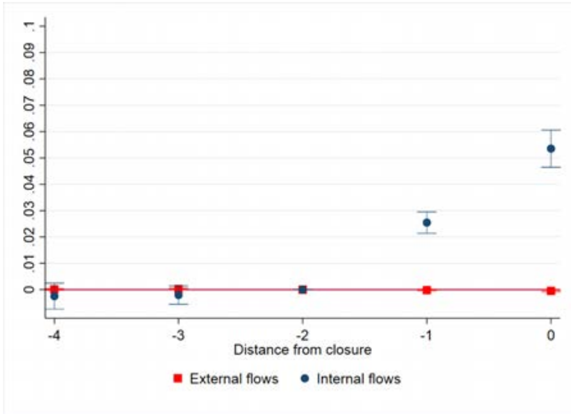


Note: The figure plots the coefficients $\widehat{\delta}_{\tau}^{Int} - \widehat{\delta}_{-2}^{Int}$ (blue dots) and $\widehat{\delta}_{\tau}^{Ext} - \widehat{\delta}_{-2}^{Ext}$ (red squares) estimated from equation (6), which measure the change in bilateral worker flows from event date -2 to event date $\tau \in [-4, 0]$, relative to the counterfactual flows. The flows are measured as the ratio of workers moving from closing BG-affiliated firm j to firm k in year t, to the total number of workers displaced by firm j in year t. Event date 0 is the last year of activity of the closing firm. The error bars show the 95% confidence intervals calculated using standard errors that are clustered at the group (of origin) level. We include firm-pair fixed effects and year dummies in our specification. Table 13 reports the estimated coefficients, standard errors and sample size.

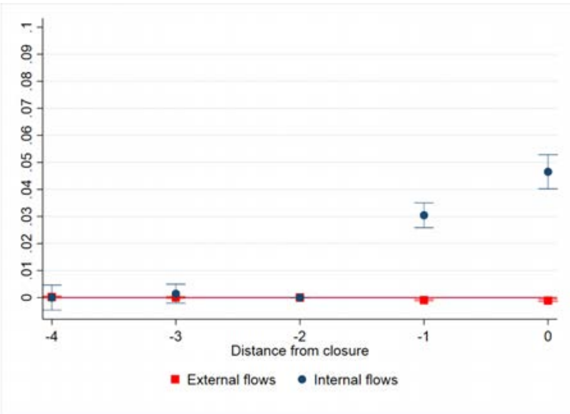
Figure 10: Impact of firm closures on ILM and ELM outflows, by occupation



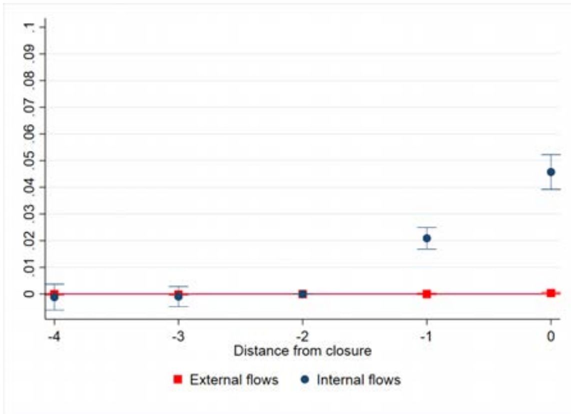
(a) Blue Collars



(b) Clerical Workers



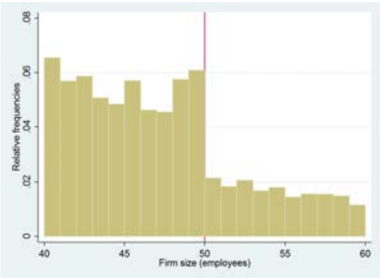
(c) Intermediate Professions



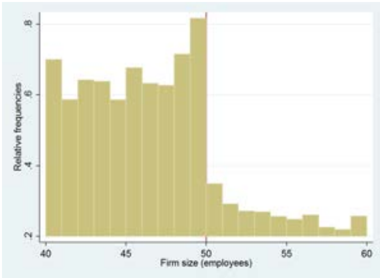
(d) Managers

Note: The figure plots the coefficients $\widehat{\delta}_\tau^{Int} - \widehat{\delta}_{-2}^{Int}$ (blue dots) and $\widehat{\delta}_\tau^{Ext} - \widehat{\delta}_{-2}^{Ext}$ (red squares) jointly estimated in a specification in which we distinguish flows within four occupational categories: blue collars, clerical workers, intermediate professions, managers/high-skill workers. The specification also includes firm-pair×occupation fixed effects and year dummies. The flows are measured as the ratio of workers *in a given occupational category* moving from a closing BG-affiliated firm j to firm k in year t, to the total number of workers displaced by firm j in year t. Event date 0 is the last year of activity of the closing firm. The error bars show the 95% confidence intervals calculated using standard errors that are clustered at the group level. At $\tau = -1$ and $\tau = 0$, the estimated coefficients $\widehat{\delta}_\tau^{Int} - \widehat{\delta}_{-2}^{Int}$ for blue collars are significantly different from the estimated coefficients for clerical workers, intermediate professions and managers/high-skill workers at 0.1% ($p = 0.0000$ for all the comparisons). Table 14 reports the estimated coefficients, standard errors and sample size.

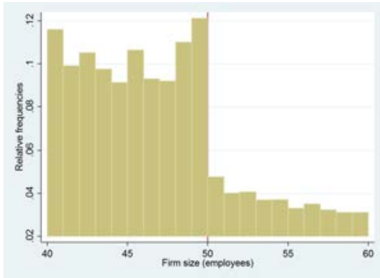
Figure 11: Firm size distribution around the 50 employee threshold (year 2006)



(a) Stand-alone firms

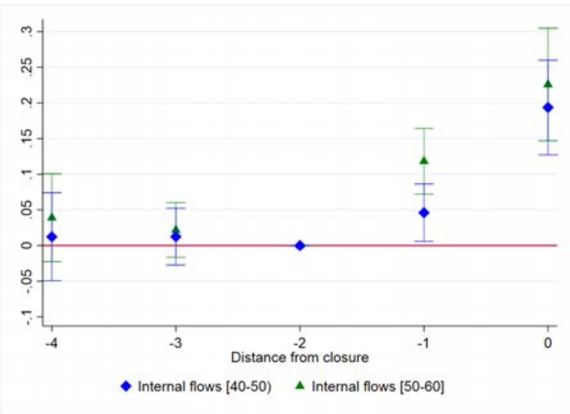


(b) Business group affiliated firms

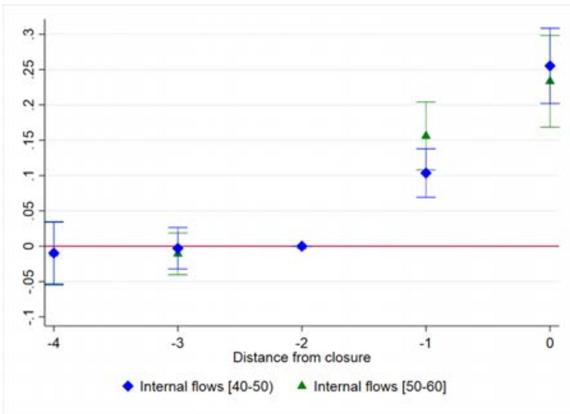


(c) All firms

Figure 12: ILM flows at closure in firms just below versus just above 50 employees



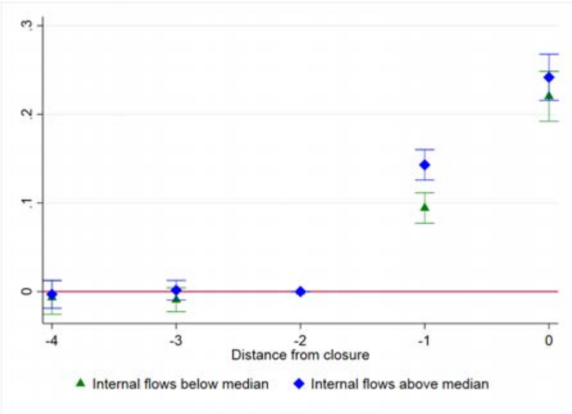
(a) Size at $\tau = 0$



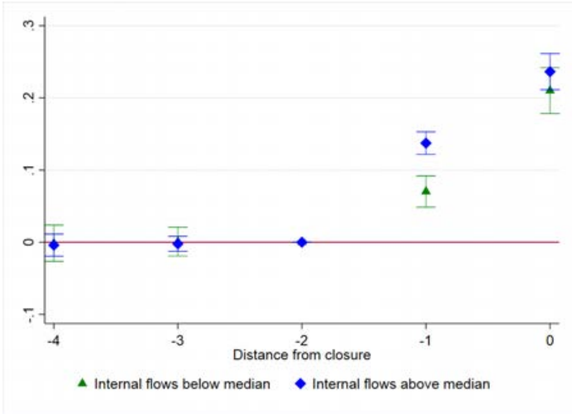
(b) Size at $\tau = -2$

Note: The figure plots the coefficients $\widehat{\delta}_{\tau}^{Int} - \widehat{\delta}_{-2}^{Int}$ estimated in equation (7). Blue diamonds represent coefficients for firms between 40 and 50 employees while green triangles for firms between 51 and 60 employees. In panel (a) firms are assigned to a size bucket based on their employment at $\tau = 0$; in panel (b) firms are assigned to a size bucket based on their employment at $\tau = -2$. The flows are measured as the ratio of workers moving from closing BG-affiliated firm j to firm k in year t, to the total number of workers displaced by firm j in year t. Event date 0 is the last year of activity of the closing firm. The error bars show the 95% confidence intervals calculated using standard errors that are clustered at the group (of origin) level. We include firm-pair fixed effects and year dummies in our specification. In panel (a) at $\tau = -1$ the coefficient $\widehat{\delta}_{\tau}^{Int} - \widehat{\delta}_{-2}^{Int}$ for firms above 50 is significantly different from the coefficient for firm below 50 (and positive) at 0.1% ($p = 0.006$). In panel (b) at $\tau = -1$ the coefficient $\widehat{\delta}_{\tau}^{Int} - \widehat{\delta}_{-2}^{Int}$ for firms above 50 is significantly different from the coefficient for firm below 50 (and positive) at 5% ($p = 0.0364$). At $\tau = 0$ the coefficients are not significantly different. Table 15 reports the estimated coefficients, standard errors and sample size.

Figure 13: Evolution of ILM flows from closing BG firms, by firm of destination characteristics



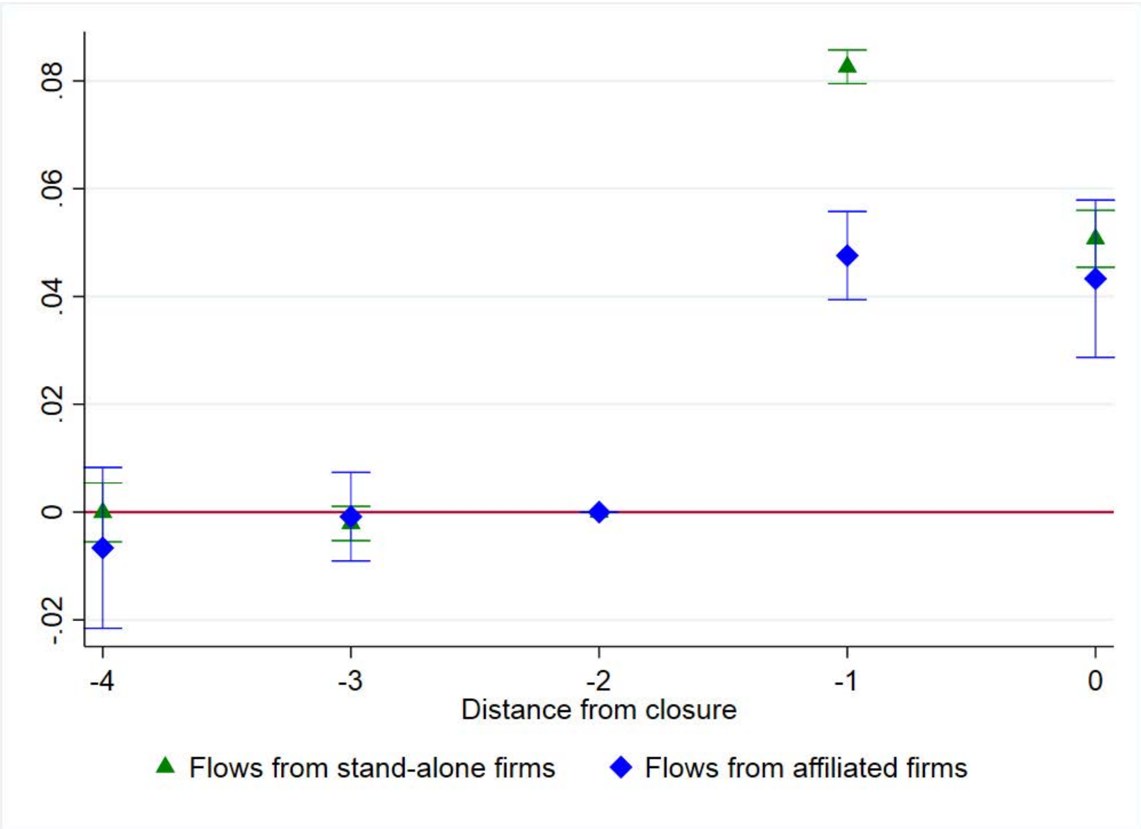
(a) Flows to ILM firms with high vs low pre-event Value Added Per Worker



(b) Flows to ILM firms with high vs low pre-event Capex

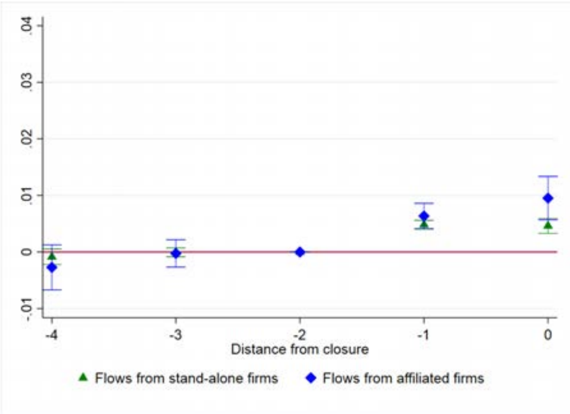
Note: The figure shows the effect of a group firm closure on bilateral worker flows from the closing BG firm to ILM partners. In panel (a), we compare flows to ILM destination firms with (average pre-event) Value Added Per Worker above the median (blue diamonds) versus below the median (green triangles). At $\tau = -1$ ILM flows to firms with high VA per Worker are significantly higher than ILM flows to firms with low VA per Worker; the difference being positive and 0.1% significant ($p = 0.0000$). In panel (b), we compare flows to ILM destination firms that have average pre-event Capex above the median (blue diamonds) versus below the median (green triangles). At $\tau = -1$ ILM flows to high Capex firms are significantly higher than ILM flows to low Capex firms: the difference is positive and 0.1% significant ($p = 0.0000$). Differences are not significant at $\tau = 0$ ($p = 0.14$ in panel (a) and $p = 0.13$ in panel (b)). The flows are measured as the ratio of workers moving from closing BG-affiliated firm j to firm k in year t, to the total number of workers displaced by firm j in year t. All destination-firm characteristics are measured taking the average over the period $\tau \in [-4, -2]$. Event date 0 is the last year of activity of the closing firm. The figure plots the change in bilateral worker flows from event date -2 to event date $\tau \in [-4, 0]$, relative to the counterfactual flows. The error bars show the 95% confidence intervals calculated using standard errors that are clustered at the group (of origin) level. We include firm-pair fixed effects and year dummies in our specification. Table 16 reports the estimated coefficients, standard errors and sample size.

Figure 14: Impact of firm closures on worker flows to unemployment

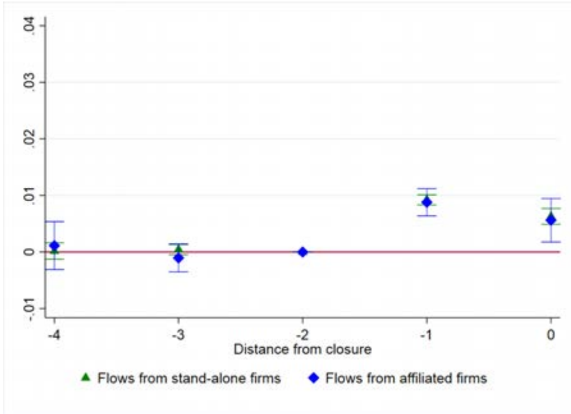


Note: The figure plots the coefficients estimated from equation (8). Blue diamonds represent coefficients for unemployment flows originating from BG firms, while green triangles represent coefficients for unemployment flows originating from SA firms. Flows to unemployment are measured as the ratio of workers moving to unemployment divided by the employment stock at $\tau = -2$. Event date 0 is the last year of activity of the closing firm. The figure plots the change in flows to unemployment from event date -2 to event date $\tau \in [-4, 0]$, relative to the counterfactual flows. The error bars show the 95% confidence intervals calculated using standard errors that are clustered at the group level for BG firms and at the firm level for stand-alone firms. We include firm fixed effects and year dummies in our specification. The difference between the coefficients of flows from SA firms and flows from BG firms is positive and significant at 0.1% ($p = 0.0000$) at $\tau = -1$, while it is not significant at $\tau = 0$. Table 17 reports the estimated coefficients, standard errors and sample size.

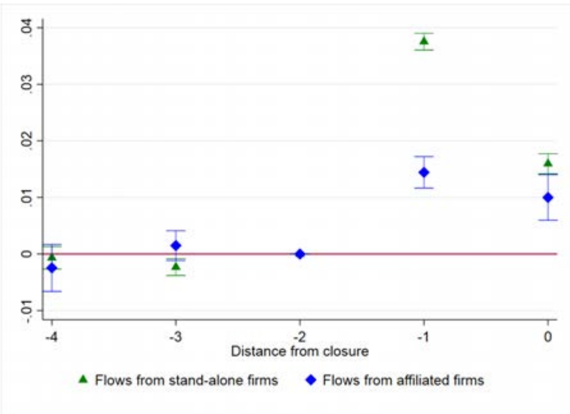
Figure 15: Impact of firm closures on worker flows to unemployment, by occupation



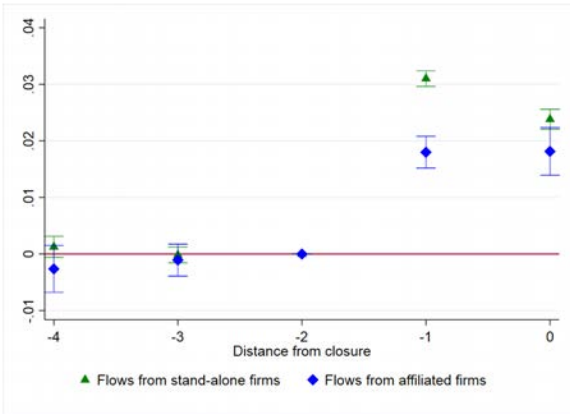
(a) Managers



(b) Intermediate Professions



(c) Clerical Workers



(d) Blue Collars

Note: The figure plots the coefficients of unemployment flows originating from SA firms (green triagles) and unemployment flows from BG firms (blue diamonds) jointly estimated in a single specification in which we distinguish flows within four occupational categories: blue collars, clerical workers, intermediate professions, managers/high-skill workers. The specification also includes firm-pair×occupation fixed effects and year dummies. Flows to unemployment are measured as the ratio of workers in a given occupation moving to unemployment divided by the firm's total employment at $\tau = -2$. Event date 0 is the last year of activity of the closing firm. The figure plots the change in flows to unemployment from event date -2 to event date $\tau \in [-4, 0]$, relative to the counterfactual flows. The error bars show the 95% confidence intervals calculated using standard errors that are clustered at the group level for BG firms and at the firm level for stand-alone firms. For blue collar workers the difference between the estimated coefficient of flows from SA firms and the coefficient of flows from BG firms is positive and significant at 0.1% ($p = 0.0000$)at $\tau = -1$, and at 5% ($p = 0.015$)at $\tau = 0$. For clerical workers the difference is positive and significant at 0.1% ($p = 0.0000$)at $\tau = -1$, and at 1% ($p = 0.008$) at $\tau = 0$. Table 18 reports the estimated coefficients, standard errors and sample size.

Table 1. Mean excess probability (unconditional) of within-group firm-to-firm transitions

	mean	sd	p10	p25	p50	p75	p90	N
2003	0.050	0.151	-0.000	-0.000	-0.000	0.010	0.140	36302
2004	0.053	0.158	-0.000	-0.000	-0.000	0.011	0.143	35594
2005	0.052	0.156	-0.000	-0.000	-0.000	0.011	0.143	37682
2006	0.053	0.156	-0.000	-0.000	-0.000	0.011	0.150	40294
2007	0.049	0.149	-0.000	-0.000	-0.000	0.008	0.143	42864
2008	0.047	0.146	-0.000	-0.000	-0.000	0.007	0.125	45672
2009	0.055	0.160	-0.000	-0.000	-0.000	0.012	0.164	39293
2010	0.057	0.169	-0.000	-0.000	-0.000	0.010	0.167	40751

Note: Unconditional excess probability: excess probability that a worker i changing job is hired by firm j if the firm of origin k is affiliated with the same group as j, as compared to a similar worker originating from some firm k outside the group. The first column indicates the year in which workers transiting from one job to another were hired by BG firm j.

Table 2. Mean excess probability of within-group firm-to-firm transitions by year

Year	Mean	St.Dev.	Percentiles 10	25	50	75	90	N	Mean	St.Dev.	Percentiles 10	25	50	75	90	N
	Panel a: Job transitions between any two ZEMPs								**Panel b: Job transitions within same ZEMP**							
2003	0.049	0.150	-0.000	-0.000	-0.000	0.010	0.125	36302	0.060	0.181	-0.000	-0.000	-0.000	0.001	0.167	34945
2004	0.053	0.159	-0.000	-0.000	-0.000	0.010	0.143	35594	0.064	0.190	-0.000	-0.000	-0.000	0.001	0.200	34152
2005	0.052	0.158	-0.000	-0.000	-0.000	0.011	0.143	37682	0.065	0.192	-0.000	-0.000	-0.000	0.002	0.200	36257
2006	0.053	0.158	-0.000	-0.000	-0.000	0.011	0.146	40294	0.066	0.192	-0.000	-0.000	-0.000	0.002	0.200	38552
2007	0.048	0.150	-0.000	-0.000	-0.000	0.008	0.125	42864	0.060	0.181	-0.000	-0.000	-0.000	0.001	0.171	41233
2008	0.047	0.147	-0.000	-0.000	-0.000	0.007	0.125	45672	0.058	0.178	-0.000	-0.000	-0.000	0.001	0.167	44060
2009	0.055	0.164	-0.000	-0.000	-0.000	0.011	0.162	39293	0.066	0.194	-0.000	-0.000	-0.000	0.002	0.200	37774
2010	0.056	0.171	-0.000	-0.000	-0.000	0.009	0.167	40751	0.065	0.193	-0.000	-0.000	-0.000	0.002	0.200	39479
	Panel c: Job transitions between any two occupations								**Panel d: Job transitions within same occupation**							
2003	0.093	0.235	-0.000	-0.000	0.000	0.015	0.333	36302	0.068	0.204	-0.000	-0.000	0.000	0.001	0.200	34057
2004	0.097	0.241	-0.000	-0.000	0.000	0.017	0.370	35594	0.072	0.211	-0.000	-0.000	0.000	0.001	0.250	33244
2005	0.098	0.242	-0.000	-0.000	0.000	0.017	0.379	37682	0.072	0.212	-0.000	-0.000	0.000	0.001	0.243	35186
2006	0.098	0.242	-0.000	-0.000	0.000	0.018	0.375	40294	0.073	0.213	-0.000	-0.000	0.000	0.001	0.250	37768
2007	0.091	0.233	-0.000	-0.000	0.000	0.011	0.333	42864	0.067	0.203	-0.000	-0.000	0.000	0.000	0.200	40242
2008	0.089	0.230	-0.000	-0.000	0.000	0.010	0.333	45672	0.068	0.205	-0.000	-0.000	0.000	0.000	0.200	43208
2009	0.101	0.247	-0.000	-0.000	0.000	0.018	0.417	39288	0.078	0.221	-0.000	-0.000	0.000	0.001	0.250	37030
2010	0.100	0.248	-0.000	-0.000	0.000	0.013	0.400	40751	0.075	0.219	-0.000	-0.000	0.000	0.001	0.250	38252
	Panel e: Job transitions between any two occupations/ZEMPS								**Panel f: Job transitions within same occupation/ZEMP**							
2003	0.100	0.246	-0.000	-0.000	0.000	0.019	0.341	36302	0.079	0.230	-0.000	-0.000	0.000	0.000	0.250	29914
2004	0.102	0.250	-0.000	-0.000	0.000	0.020	0.417	35594	0.082	0.236	-0.000	-0.000	0.000	0.000	0.278	29175
2005	0.104	0.251	-0.000	-0.000	0.000	0.021	0.431	37682	0.082	0.236	-0.000	-0.000	0.000	0.000	0.274	31034
2006	0.104	0.251	-0.000	-0.000	0.000	0.022	0.417	40293	0.084	0.238	-0.000	-0.000	0.000	0.000	0.333	32976
2007	0.100	0.243	-0.000	-0.000	0.000	0.014	0.333	42864	0.078	0.229	-0.000	-0.000	0.000	0.000	0.250	35695
2008	0.094	0.240	-0.000	-0.000	0.000	0.013	0.333	45672	0.078	0.228	-0.000	-0.000	0.000	0.000	0.250	38282
2009	0.110	0.256	-0.000	-0.000	0.000	0.023	0.500	39282	0.087	0.243	-0.000	-0.000	0.000	0.000	0.333	32798
2010	0.104	0.255	-0.000	-0.000	0.000	0.017	0.441	40746	0.080	0.232	-0.000	-0.000	0.000	0.000	0.250	34770

Note: The table displays estimated excess probabilities $\widehat{\gamma_{c,j,t}}$ first averaged at the firm level and then by year. In panel (a) the estimated excess probabilities $\widehat{\gamma}_{c,j,t}$ control for firm of destination × local labor market pair specific effect; adding the condition that location of origin=location of destination yields the excess probabilities in panel (b). In panel (c) estimated excess probabilities $\widehat{\gamma}_{c,j,t}$ control for firm of destination × occupation pair specific effect: adding the condition that occupation of origin = occupation of destination yields the excess probabilities in panel (d). In panel (e), estimated excess probabilities $\widehat{\gamma}_{c,j,t}$ control for firm of destination × occupation pair × location pair specific effect; in panel (f) we impose same location/occupation of origin and destination. The first column indicates the year in which workers transiting from one job to another were hired by BG firm j.

Table 3. Mean excess probability of within-group job-to-job transitions. Rankings by two-digit occupation of origin/destination

Occupation of origin	Code	Mean	**Occupation of destination**	Code	Mean
CEOs of firms with more than 10 employees	23	0.03623	CEOs of firms with more than 10 employees	23	0.04009
CEOs of industrial/commercial firms with less than 10 employees	22	0.03183	CEOs of industrial/commercial firms with less than 10 employees	22	0.03539
Administrative/commercial managers	37	0.02567	CEOs of artisan firms	21	0.03080
Doctors, lawyers, accountants and other professionals	31	0.02502	Administrative/commercial managers	37	0.02497
Engineers and technical managers	38	0.02485	Foremen	48	0.02463
Foremen	48	0.02287	Doctors, lawyers, accountants and other professionals	31	0.02271
CEOs of artisan 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 skilled workers	65	0.02142
Technicians	47	0.02106	Agricultural workers	69	0.02004
Teachers, librarians, other occ. in education	42	0.01991	Technicians	47	0.01996
Intermediate administrative/commercial occupations	46	0.01980	Intermediate administrative/commercial occupations	46	0.01906
Agricultural workers	69	0.01979	Surveillance and security occupations	53	0.01857
Surveillance and security occupations	53	0.01836	Teachers, librarians, other occ. in education	42	0.01823
Artisan skilled workers	63	0.01735	Journalists, media/arts/entertainment occupations	35	0.01758
Clerical support	54	0.01726	Industrial skilled workers	62	0.01753
Healthcare support occupations and social services	43	0.01723	Clerical support	54	0.01713
Industrial skilled workers	62	0.01716	Industrial non skilled workers	67	0.01679
Journalists, media/arts/entertainment occupations	35	0.01682	Healthcare support occupations and social services	43	0.01679
Artisan non skilled workers	68	0.01680	Artisan non skilled workers	68	0.01652
Drivers	64	0.01603	Artisan skilled workers	63	0.01644
Industrial non skilled workers	67	0.01494	Sales and related occupations	55	0.01544
Sales and related occupations	55	0.01479	Drivers	64	0.01466
Personal service and personal care occ.	56	0.01077	Personal service and personal care occ.	56	0.01448

Note: The table ranks two-digit occupation categories according to ILM activity, as measured by the estimated excess probabilities. The third column in each panel reports, for a given occupation, the average of all the $\widehat{\gamma}_{c,j,t}$ with that occupation as the occupation of origin (left hand side panel) and destination (right hand side panel). Rankings are net of year effects and firm fixed effects.

Table 4. Heterogeneity of ILM activity (excess probabilities) by occupation

Variables	(1)	(2)	(3)
(Log) Firm Size	0.008***	0.008***	0.008***
	(0.001)	(0.001)	(0.001)
(Log) Rest of the group size	-0.010***	-0.010***	-0.010***
	(0.002)	(0.002)	(0.002)
(Log) Number of affiliated firms	-0.014***	-0.014***	-0.014***
	(0.003)	(0.003)	(0.003)
State Control	-0.011**	-0.011**	-0.011**
	(0.004)	(0.004)	(0.004)
Foreign Control	-0.031***	-0.031***	-0.030***
	(0.005)	(0.005)	(0.005)
Occupation of destination (Managers excluded)			
Intermediate Profession	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)
Clerical Worker	-0.005***	-0.005***	-0.005***
	(0.001)	(0.001)	(0.001)
Blue Collar	-0.004***	-0.004***	-0.003***
	(0.001)	(0.001)	(0.001)
Occupation of origin (Managers excluded)			
Intermediate Profession	-0.003***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.000)
Clerical Worker	-0.006***	-0.006***	-0.005***
	(0.001)	(0.001)	(0.001)
Blue Collar	-0.005***	-0.005***	-0.004***
	(0.001)	(0.001)	(0.001)
Same Occupation		-0.002***	0.001***
		(0.000)	(0.000)
Same Occupation × Intermediate Profession			-0.002***
			(0.000)
Same Occupation × Clerical Worker			-0.005***
			(0.000)
Same Occupation × Blue Collar			-0.007***
			(0.000)
N	8,992,670	8,992,670	8,992,670
Firm × Group and year dummies	Yes	Yes	Yes

Note: The dependent variable is the estimated excess probability $\widehat{\gamma}_{c,j,t}$ for a given occupational pair and firm j in year t. *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. We organize the occupational categories listed in Table A1 (Appendix A.2) into four groups: managers, intermediate professions, clerical workers, blue collars. *Same Occupation* is a dummy variable taking the value 1 if the occupation of origin is equal to the occupation of destination. We control for firm × group fixed effects, and include year dummies to control for macroeconomic shocks common to all firms. 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 5. Impact of large competitor closures on worker flows from ELM and ILM firms

	Baseline		Sectoral trends		Different definition of closures		[-2,+2] Window	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Distance from shock	External flows	Internal flows	External flows	Internal flows	External flows	Internal flows	External flows	Internal flows
-3	0.00019	0.00436	0.00005	0.00444	0.00000	0.00566		
	(0.00021)	(0.00277)	(0.00022)	(0.00289)	(0.00020)	(0.00310)		
-2	0.00019	0.00274	0.00014	0.00276	0.00006	0.00398	0.00016	0.00378
	(0.00012)	(0.00207)	(0.00013)	(0.00249)	(0.00011)	(0.00227)	(0.00012)	(0.00212)
-1	-	-	-	-	-	-	-	-
	(-)	(-)	(-)	(-)	(-)	(-)	(-)	(-)
0	0.00025**	0.00517*	0.00029**	0.00516	0.00024**	0.00468*	0.00027**	0.00492*
	(0.00009)	(0.00230)	(0.00011)	(0.00293)	(0.00008)	(0.00221)	(0.00009)	(0.00231)
1	0.00016	0.01167***	0.00024	0.01163**	0.00008	0.01091***	0.00019	0.01109***
	(0.00019)	(0.00294)	(0.00017)	(0.00358)	(0.00018)	(0.00262)	(0.00019)	(0.00287)
2	-0.00026	0.01543**	0.00007	0.01545*	-0.00033	0.01426**	-0.00021	0.01422**
	(0.00026)	(0.00525)	(0.00028)	(0.00672)	(0.00024)	(0.00537)	(0.00024)	(0.00524)
3	-0.00022	0.01603***	-0.00001	0.01607**	-0.00037	0.01780***		
	(0.00033)	(0.00439)	(0.00023)	(0.00536)	(0.00035)	(0.00437)		
Pair FE	Yes		Yes		Yes		Yes	
N	2975794		2975794		2886782		2975794	

Note: The table reports the coefficients $\widehat{\alpha}_{\tau}^{Int} - \widehat{\alpha}_{-1}^{Int}$ and $\widehat{\alpha}_{\tau}^{Ext} - \widehat{\alpha}_{-1}^{Ext}$ estimated from equation (3). Date $\tau = 0$ is the year of the positive shock, i.e. the first year in which the large competitor is no longer active in a given industry. The flows are measured as the ratio of workers hired by a BG-affiliated firm j (active in a shocked industry) from firm k in year t, to the total number of workers hired by firm j in year t. We include firm-pair fixed effects and year dummies in our specification. Columns (1) and (2) show estimated coefficients in our benchmark specification. Columns (3)-(8) explore robustness to: (i) including sectoral trends; (ii) using a stricter definition of closures (not labeling as closures cases where more than 50% of the lost employment ends up in another single firm); (iii) focusing on a shorter event window. Standard errors in parenthesis are clustered at the industry and group level. Significance levels are * 5%, ** 1%, *** 0.1%. The total number of observations in columns (1)-(4) and (7)-(8) is 2978549 (see also Table A8); however, 2755 are singletons and do not contribute to the estimation of the coefficients.

Table 6. Impact of large competitor closures on worker flows from ELM and ILM firms, same/different local labor market and industry

	Different Zone d'emploi		Same Zone d'emploi		Different 4d Sector		Same 4d Sector	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Distance from shock	External Flows	Internal Flows	External Flows	Internal Flows	External Flows	Internal Flows	External Flows	Internal Flows
-3	0.00012	0.00362	0.00057	0.00575	0.00052**	0.00610	0.00031	-0.00411
	(0.00030)	(0.00357)	(0.00082)	(0.00535)	(0.00017)	(0.00600)	(0.00103)	(0.00438)
-2	0.00011	0.00123	0.00024	0.00325	0.00010	0.00836*	0.00088	-0.00654
	(0.00016)	(0.00261)	(0.00055)	(0.00345)	(0.00020)	(0.00356)	(0.00097)	(0.00336)
-1	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-
0	-0.00008	0.00839**	0.00024	0.00111	0.00015	0.01202**	-0.00148	-0.00060
	(0.00030)	(0.00300)	(0.00068)	(0.00400)	(0.00013)	(0.00387)	(0.00159)	(0.00391)
1	0.00043	0.01144***	-0.00106	0.01195**	0.00051	0.01333**	-0.00020	0.00879*
	(0.00070)	(0.00283)	(0.00116)	(0.00447)	(0.00029)	(0.00517)	(0.00160)	(0.00442)
2	0.00007	0.01389**	-0.00172*	0.01782*	-0.00013	0.02342***	0.00178	0.00288
	(0.00054)	(0.00521)	(0.00081)	(0.00760)	(0.00035)	(0.00495)	(0.00161)	(0.00521)
3	-0.00045	0.01565**	-0.00207	0.01585*	-0.00023	0.01308**	0.00177	0.01702*
	(0.00055)	(0.00545)	(0.00106)	(0.00771)	(0.00044)	(0.00494)	(0.00204)	(0.00718)
Pair FE	Yes				Yes			
N	2455683				2382528			

Note: The left part of the table reports the coefficients $\widehat{\alpha}_{\tau}^{Int} - \widehat{\alpha}_{-1}^{Int}$ and $\widehat{\alpha}_{\tau}^{Ext} - \widehat{\alpha}_{-1}^{Ext}$ estimated in a single specification in which we distinguish flows within pairs of firms where the firm of origin operates in a different local labor market than firm j (estimates displayed in columns (1)-(2)) and flows within pairs where the firm of origin operates in the same local labor market as firm j (estimates displayed in columns (3)-(4)). The right part of the table reports the coefficients estimated in a single specification in which we distinguish flows within pairs of firms where the firm of origin operates in a different 4 digit industry (estimates displayed in columns (5)-(6)) and flows within pairs where the firm of origin operates in the same 4 digit industry as firm j (estimates displayed in columns (7)-(8)). Date $\tau = 0$ is the year of the positive shock, i.e. the first year in which the large competitor is no longer active in a given industry. We include firm-pair fixed effects and year dummies in our specification. The flows are measured as the ratio of workers hired by a BG-affiliated firm j (active in a shocked industry) from firm k in year t, to the total number of workers hired by firm j in year t. We include firm-pair fixed effects and year dummies in our specification. Standard errors in parenthesis are clustered at the industry and group level. Significance levels are * 5%, ** 1%, *** 0.1%.

Table 7. Impact of large competitor closures on market share of shocked firms, by ILM Access

	ILM Access							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Distance from shock	Below Median	Above Median	Below Median	Top Quartile	Below Median	Top Decile	Below Median	95th percentile
-3	0.00010	0.00022	0.00020	0.00012	0.00024	-0.00138	0.00019	-0.00420
	(0.00019)	(0.00038)	(0.00023)	(0.00073)	(0.00023)	(0.00137)	(0.00024)	(0.00253)
-2	0.00008	-0.00003	0.00011	-0.00019	0.00016	-0.00139	0.00015	-0.00298*
	(0.00011)	(0.00023)	(0.00013)	(0.00045)	(0.00012)	(0.00075)	(0.00012)	(0.00144)
-1	-	-	-	-	-	-	-	-
	(-)	(-)	(-)	(-)	(-)	(-)	(-)	(-)
0	-0.00010	0.00116***	-0.00015	0.00226***	-0.00016	0.00446**	-0.00017	0.00566**
	(0.00027)	(0.00032)	(0.00030)	(0.00064)	(0.00030)	(0.00137)	(0.00037)	(0.00191)
1	-0.00025	0.00148***	-0.00032	0.00296***	-0.00028	0.00569***	-0.00032	0.00810**
	(0.00030)	(0.00043)	(0.00035)	(0.00085)	(0.00036)	(0.00169)	(0.00037)	(0.00266)
2	-0.00033	0.00142**	-0.00044	0.00296**	-0.00034	0.00566**	-0.00040	0.00809**
	(0.00033)	(0.00047)	(0.00040)	(0.00096)	(0.00041)	(0.00177)	(0.00041)	(0.00296)
3	-0.00010	0.00118*	-0.00023	0.00252*	-0.00013	0.00418*	-0.00019	0.00502
	(0.00034)	(0.00056)	(0.00041)	(0.00113)	(0.00042)	(0.00200)	(0.00042)	(0.00336)
Firm FE	Yes		Yes		Yes		Yes	
N	51632		38127		30654		28178	

Note: The table reports the effects of large competitor closures on the market share of BG firms in shocked industries, for firms with different levels of *ILM Access* (see equation 4). Date $\tau = 0$ is the year of the positive shock, i.e. the first year in which the large competitor is no longer active in a given industry. We report estimates of the changes in market share from event date -1 to event date $\tau \in [-3, +3]$, for shocked firms with *ILM Access* below median; with *ILM Access* above median (column (2)); in the top quartile of the *ILM Access* distribution (column (4)); in the top decile of the *ILM Access* distribution (column (6)); in the top 5 percent of the *ILM Access* distribution (column (8)). The median value of *ILM Acces* is equal to 1 worker, the 75th percentile is equal to 35 workers; the 90th percentile is equal to 207 workers, the 95th percentile to 919 workers. We include firm fixed effects and year dummies in our specification. Standard errors in parenthesis are clustered at the industry and group level. Significance levels are * 5%, ** 1%, *** 0.1%.

Table 8. Impact of large competitor closures on return on assets (ROA) of shocked firms, by ILM Access

	ILM Access							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Distance from shock	Below Median	Above Median	Below Median	Top Quartile	Below Median	Top Decile	Below Median	95th Percentile
-3	0.00125	-0.00113	0.00111	-0.00099	0.00086	0.00312	0.00129	0.00346
	(0.00345)	(0.00336)	(0.00349)	(0.00315)	(0.000340)	(0.00345)	(0.00335)	(0.00731)
-2	-0.00001	-0.00022	0.00007	-0.000243	0.00002	0.00164	0.00020	0.01005
	(0.00197)	(0.00205)	(0.00194)	(0.00304)	(0.00193)	(0.00434)	(0.00192)	(0.00842)
-1	-	-	-	-	-	-	-	-
	(-)	(-)	(-)	(-)	(-)	(-)	(-)	(-)
0	-0.00062	-0.00081	-0.00097	0.00209	-0.00093	0.00648	-0.00102	0.01358*
	(0.00237)	(0.00177)	(0.00230)	(0.00336)	(0.00278)	(0.00484)	(0.00271)	(0.00672)
1	-0.00293	-0.00243	-0.00390	0.00172	-0.00367	0.01144*	-0.00377	0.02257***
	(0.00293)	(0.00216)	(0.00288)	(0.00291)	(0.00278)	(0.00484)	(0.00271)	(0.00672)
2	-0.01010*	-0.01219*	-0.01187**	-0.00275	-0.01165**	-0.00007	-0.01201**	0.01232
	(0.00402)	(0.00558)	(0.00428)	(0.00486)	(0.00435)	(0.00634)	(0.00347)	(0.00848)
3	-0.00210	-0.00743	-0.00403	0.00160	-0.00384	0.00651	-0.00438	0.02206**
	(0.00310)	(0.00596)	(0.00307)	(0.00535)	(0.00323)	(0.00643)	(0.00335)	(0.00717)
Firm FE	Yes		Yes		Yes		Yes	
N	45387		33474		26999		24807	

Note: The table reports the effects of large competitor closures on the return on assets (ROA) of BG firms in shocked industries, for firms with different levels of *ILM Access* (see equation 4). Date $\tau = 0$ is the year of the positive shock, i.e. the first year in which the large competitor is no longer active in a given industry. We report estimates of the changes in ROA from event date -1 to event date $\tau \in [-3, +3]$, for shocked firms with *ILM Access* below median; with *ILM Access* above median (column (2)); in the top quartile of the *ILM Access* distribution (column (4)); in the top decile of the *ILM Access* distribution (column (6)); in the top 5 percent of the *ILM Access* distribution (column (8)). The median value of *ILM Acces* is equal to 1 worker, the 75th percentile is equal to 35 workers; the 90th percentile is equal to 207 workers, the 95th percentile to 919 workers. We include firm fixed effects and year dummies in our specification. Standard errors in parenthesis are clustered at the industry and group level. Significance levels are * 5%, ** 1%, *** 0.1%.

Table 9. Impact of large competitor closures on worker flows from ILM firms, by firm of origin characteristics

	VA per worker		Capex	
	(1)	(2)	(3)	(4)
Distance from shock	Below Median	Above Median	Below Median	Above Median
-3	0.01028**	-0.00352	0.01029*	-0.00094
	(0.00329)	(0.00390)	(0.00482)	(0.00382)
-2	0.00232	0.00244	0.00336	0.00235
	(0.00326)	(0.00291)	(0.00311)	(0.00297)
-1	-	-	-	-
	(-)	(-)	(-)	(-)
0	0.01318***	-0.00380	0.01040**	0.00120
	(0.00369)	(0.00416)	(0.00392)	(0.00365)
1	0.01750***	0.00526	0.02128***	0.00455
	(0.00419)	(0.00466)	(0.00559)	(0.00401)
2	0.01760*	0.01089	0.02612*	0.00572
	(0.00741)	(0.00622)	(0.01048)	(0.00472)
3	0.01648***	0.01648*	0.03004***	0.00764
	(0.00500)	(0.00736)	(0.00787)	(0.00631)
PairFE	Yes		Yes	
N	57696		57835	

Note: The table reports the effects of large competitor closures on firm-to-firm worker flows to BG firms in shocked industries, originating from ILM partners with: Value Added Per Worker below/above median (coefficients displayed in columns (1)-(2)); Capex (capital expenditures) below/above median (coefficients displayed columns (3)-(4)). All firm of origin characteristics are measured as pre-event averages, taking the average over the pre-treatment period within the event window, i.e. over years $\tau \in [-3, 0)$. Date $\tau = 0$ is the year of the positive shock, i.e. the first year in which the large competitor is no longer active in a given industry. We report estimates of the changes in ILM flows from event date -1 to event date $\tau \in [-3, +3]$. The flows are measured as the ratio of workers hired by a BG-affiliated firm j (active in a shocked industry) from firm k in year t, to the total number of workers hired by firm j in year t. We include firm-pair fixed effects and year dummies in our specification. Standard errors in parenthesis are clustered at the industry and group level. Significance levels are * 5%, ** 1%, *** 0.1%. The coefficients in columns (1) and (2) are significantly different at 1% at $\tau = 0$ ($p = 0.0075$) and at 5% at $\tau = 1$ ($p = 0.03$). The coefficients in columns (3) and (4) are significantly different at 5% at $\tau = 1$ ($p = 0.017$), $\tau = 2$ ($p = 0.044$), and $\tau = 3$ ($p = 0.025$).

Table 10. Impact of large competitor closures on worker flows from ELM and ILM firms, by occupation

	Blue Collars		Clerical Support		Intermediate		Managers/High-Skill	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Distance from shock	External Flows	Internal Flows	External Flows	Internal Flows	External Flows	Internal Flows	External Flows	Internal Flows
-3	-0.00012	0.00217	0.00006	-0.00083	0.00008	0.00210	0.00016	0.00192
	(0.00020)	(0.00179)	(0.00015)	(0.00126)	(0.00012)	(0.00111)	(0.00010)	(0.00200)
-2	-0.00009	0.00229*	0.00013	-0.00046	-0.00005	-0.00006	0.00021**	0.00147
	(0.00010)	(0.00113)	(0.00011)	(0.00123)	(0.00010)	(0.00125)	(0.00008)	(0.00128)
-1	-	-	-	-	-	-	-	-
	(-)	(-)	(-)	(-)	(-)	(-)	(-)	(-)
0	0.00021	0.00387**	0.00036***	0.00037	-0.00023	0.00062	-0.00010	0.00112
	(0.00012)	(0.00144)	(0.00021)	(0.00096)	(0.00018)	(0.00133)	(0.00015)	(0.00118)
1	0.00006	0.00486***	0.00062**	0.00355*	-0.00040**	0.00077	-0.00013	0.00344*
	(0.00012)	(0.00132)	(0.00023)	(0.00159)	(0.00013)	(0.00147)	(0.00015)	(0.00170)
2	-0.00036	0.00430*	0.00053*	0.00583*	-0.00040*	0.00054	-0.00001	0.00445*
	(0.00022)	(0.00168)	(0.00026)	(0.00263)	(0.00016)	(0.00162)	(0.00014)	(0.00189)
3	-0.00007	0.00265	0.00038	0.00284	-0.00029	0.00606**	-0.00024	0.00455*
	(0.00021)	(0.00232)	(0.00024)	(0.00216)	(0.00021)	(0.00209)	(0.00018)	(0.00194)
Pair × Occup. FE	Yes							
N	11853776							

Note: The table reports the coefficients $\widehat{\alpha}_{\tau}^{Int} - \widehat{\alpha}_{-1}^{Int}$ and $\widehat{\alpha}_{\tau}^{Ext} - \widehat{\alpha}_{-1}^{Ext}$ estimated from equation (5). Columns (1)-(2) show estimated coefficients for blue collar worker flows, columns (3)-(4) for clerical worker flows, columns (5)-(6) for intermediate professionals and columns (7)-(8) for managers and high-skill workers. Event date 0 is the year of the positive shock, i.e. the first year in which the large competitor is no longer active in a given industry. The flows are measured as the ratio of workers *in a given occupational category* hired by a BG-affiliated firm j (active in a shocked industry) from firm k in year t, to the total number of workers hired by firm j in year t. We include firm-pair × occupation fixed effects and year dummies in our specification. Standard errors in parenthesis are clustered at the industry and group level. Significance levels are * 5%, ** 1%, *** 0.1%.

Table 11. Impact of large competitor closures on worker flows from ELM and ILM firms, for selected occupation sub-categories

	Engineers and Technical Managers		Administration Managers		Skilled Blue Collars		Unskilled Blue Collars	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Distance from shock	External Flows	Internal Flows	External Flows	Internal Flows	External Flows	Internal Flows	External Flows	Internal Flows
-3	0.00005	0.00170	0.00003	-0.00014	-0.00027	0.00204	0.00011	-0.00016
	(0.00005)	(0.00087)	(0.00007)	(0.00155)	(0.00017)	(0.00156)	(0.00009)	(0.00060)
-2	0.00011*	0.00100	0.00005	-0.00002	-0.00014	0.00188	0.00002	0.00010
	(0.00004)	(0.00091)	(0.00006)	(0.00103)	(0.00010)	(0.00104)	(0.00006)	(0.00078)
-1	-	-	-	-	-	-	-	-
	(-)	(-)	(-)	(-)	(-)	(-)	(-)	(-)
0	-0.00010	0.00053	0.00004	0.00053	0.00021	0.00254*	0.00006	0.00135
	(0.00011)	(0.00097)	(0.00006)	(0.00087)	(0.00011)	(0.00102)	(0.00008)	(0.00073)
1	-0.00012	0.00197*	0.00007	0.00096	0.00008	0.00344*	0.00009	0.00108
	(0.00010)	(0.00080)	(0.00008)	(0.00128)	(0.00011)	(0.00135	(0.00009)	(0.00056)
2	0.00001	0.00265*	0.00010	0.00101	-0.00023	0.00282*	-0.00001	0.00133
	(0.00011)	(0.00112)	(0.00010)	(0.00134)	(0.00018)	(0.00136)	(0.00009)	(0.00084)
3	-0.00011	0.00361***	-0.00003	0.00131	-0.00000	0.0016	0.00007	0.00120
	(0.00010)	(0.00104)	(0.00014)	(0.00127)	(0.00017)	(0.00191)	(0.00013)	(0.00122)
Pair × Occup. FE	Yes							
N	14817220							

Note: The table reports the coefficients $\widehat{\alpha}_{\tau}^{Int} - \widehat{\alpha}_{-1}^{Int}$ and $\widehat{\alpha}_{\tau}^{Ext} - \widehat{\alpha}_{-1}^{Ext}$ estimated from equation (5) on 10 occupation subcategories. We report here the results for the following four subcategories: Engineers and Technical Managers (columns (1)-(2)); Administration Managers (columns (3)-(4)); Skilled Blue Collars (columns (5)-(6)); Unskilled Blue Collars (columns (7)-(8)). Coefficient estimates for the other six occupation subcategories are available upon request. Event date 0 is the year of the positive shock, i.e. the first year in which the large competitor is no longer active in a given industry. The flows are measured as the ratio of workers *in a given occupational category* hired by a BG-affiliated firm j (active in a shocked industry) from firm k in year t, to the total number of workers hired by firm j in year t. We include firm-pair × occupation fixed effects and year dummies in our specification. Standard errors in parenthesis are clustered at the industry and group level. Significance levels are * 5%, ** 1%, *** 0.1%.

Table 12. Impact of large competitor closures on worker flows from ELM and ILM firms, by worker age

	Young		Old	
	(1)	(2)	(3)	(4)
Distance from shock	External Flows	Internal Flows	External Flows	Internal Flows
-3	0.00003	0.00364	0.00016	0.00077
	(0.00016)	(0.00212)	(0.00015)	(0.00177)
-2	0.00014	0.00056	0.00006	0.00222
	(0.00012)	(0.00204)	(0.00009)	(0.00157)
-1	-	-	-	-
	(-)	(-)	(-)	(-)
0	0.00010	0.00175	0.00015	0.00351^{*}
	(0.00009)	(0.00177)	(0.00009)	(0.00142)
1	-0.00020	0.00272	0.00036	0.00904^{***}
	(0.00014)	(0.00187)	(0.00020)	(0.00161)
2	-0.00039^{*}	0.00703^{*}	0.00014	0.00846^{**}
	(0.00018)	(0.00336)	(0.00018)	(0.00280)
3	-0.00051^{*}	0.00385	0.00029	0.01232^{***}
	(0.00023)	(0.00270)	(0.00023)	(0.00274)
Pair × AgeGroup FE	Yes			
N	5951424			

Note: The table reports the coefficients $\widehat{\alpha}_{\tau}^{Int} - \widehat{\alpha}_{-1}^{Int}$ and $\widehat{\alpha}_{\tau}^{Ext} - \widehat{\alpha}_{-1}^{Ext}$ estimated in a specification in which we distinguish flows of workers under 40 years of age (columns (1)-(2)) and flows of workers over 40 years of age (columns (3)-(4)). Event date 0 is the year of the positive shock, i.e. the first year in which the large competitor is no longer active in a given industry. The flows are measured as the ratio of workers *in a given age category* hired by a BG-affiliated firm j (active in a shocked industry) from firm k in year t, to the total number of workers hired by firm j in year t. We include firm-pair × age group fixed effects and year dummies in our specification. Standard errors in parenthesis are clustered at the industry and group level. Significance levels are * 5%, ** 1%, *** 0.1%.

Table 13. Impact of group-affiliated firm closures on worker flows from closing firms to ELM and ILM firms

	Baseline		Normalization at -4		Different definition of closures	
	(1)	(2)	(3)	(4)	(5)	(6)
Distance from shock	External flows	Internal flows	External flows	Internal flows	External flows	Internal flows
-4	0.00055	-0.00426	-	-	0.00055	-0.00501
	(0.00037)	(0.00737)	(-)	(-)	(0.00039)	(0.00761)
-3	0.00027	-0.00352	0.00153***	0.00172	0.00029	-0.00428
	(0.00022)	(0.00477)	(0.00020)	(0.00440)	(0.00023)	(0.00498)
-2	-	-	0.00257***	0.01410	-	-
	(-)	(-)	(0.00033)	(0.00726)	(-)	(-)
-1	-0.00246***	0.12156***	0.00079	0.11569***	-0.00260***	0.12789***
	(0.00039)	(0.00673)	(0.00050)	(0.01147)	(0.00043)	(0.00724)
0	-0.00329***	0.22586***	0.00065	0.19850***	-0.00288***	0.21835***
	(0.00060)	(0.01134)	(0.00067)	(0.01730)	(0.00063)	(0.01173)
Pair FE	Yes		Yes		Yes	
N	1894671		1433654		1751337	

Note: Columns (1)-(2) of the table reports the coefficients $\widehat{\delta}_{\tau}^{Int} - \widehat{\delta}_{-2}^{Int}$ and $\widehat{\delta}_{\tau}^{Ext} - \widehat{\delta}_{-2}^{Ext}$ estimated from equation (6), which measure the change in bilateral worker flows from event date -2 to event date $\tau \in [-4, 0]$, relative to the counterfactual flows. The flows are measured as the ratio of workers moving from closing BG-affiliated firm j to firm k in year t, to the total number of workers displaced by firm j in year t. Event date 0 is the last year of activity of the closing firm. Columns (3)-(4) explore robustness to an alternative specification where the reference year is 4 years before the closure (and accordingly BG status is defined based on affiliation at $\tau = -4$), and report estimates of the changes in worker flows from event date -4 to event dates $\tau \in [-4, 0]$. Columns (5)-(6) explore robustness to using a stricter definition of closures (not labeling as closures cases where more than 50% of the lost employment ends up in another single firm). We include firm-pair fixed effects and year dummies in our specification. Standard errors in parenthesis are clustered at the group level. Significance levels are * 5%, ** 1%, *** 0.1%.

Table 14. Impact of group-affiliated firm closures on worker flows from closing firms to ELM and ILM firms, by occupation

	Blue collars		Clerical Support		Intermediate		Managers	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Distance from the shock	External Flows	Internal Flows	External Flows	Internal Flows	External Flows	Internal Flows	External Flows	Internal Flows
-4	0.00033*	-0.00060	0.00012	-0.00248	0.00019	-0.00000	-0.00009	-0.00118
	(0.00017)	(0.00261)	(0.00015)	(0.00250)	(0.00016)	(0.00236)	(0.00013)	(0.00247)
-3	0.00016	-0.00192	0.00025	-0.00206	0.00003	0.00143	-0.00017	-0.00097
	(0.00014)	(0.00216)	(0.00013)	(0.00180)	(0.00013)	(0.00179)	(0.00011)	(0.00192)
-2	-	-	-	-	-	-	-	-
	(-)	(-)	(-)	(-)	(-)	(-)	(-)	(-)
-1	-0.00135***	0.04477***	-0.00017	0.02546***	-0.00095***	0.03044***	0.00001	0.02089***
	(0.00023)	(0.00378)	(0.00013)	(0.00206)	(0.00015)	(0.00235)	(0.00012)	(0.00208)
0	-0.00198***	0.08008***	-0.00051**	0.05354***	-0.00112***	0.04652***	0.00033*	0.04572***
	(0.00028)	(0.00544)	(0.00017)	(0.00360)	(0.00020)	(0.00321)	(0.00016)	(0.00332)
Pair × Occupation FE	Yes							
N	7578516							

Note: The table reports the coefficients $\widehat{\delta}_{\tau}^{Int} - \widehat{\delta}_{-2}^{Int}$ and $\widehat{\delta}_{\tau}^{Ext} - \widehat{\delta}_{-2}^{Ext}$ estimated in a single specification in which we distinguish flows within four occupational categories. Columns (1)-(2) report estimates for blue collar worker flows, columns (3)-(4) for clerical worker flows, columns (5)-(6) for intermediate professionals and columns (7)-(8) for managers and high-skill workers. The flows are measured as the ratio of workers *in a given occupational category* moving from a closing BG-affiliated firm j to firm k in year t, to the total number of workers displaced by firm j in year t. Event date 0 is the last year of activity of the closing firm. We include firm-pair×occupation fixed effects and year dummies in our specification. Standard errors in parenthesis are clustered at the group level. Significance levels are * 5%, ** 1%, *** 0.1%. At $\tau = -1$ and $\tau = 0$, the estimated coefficients $\widehat{\delta}_{\tau}^{Int} - \widehat{\delta}_{-2}^{Int}$ for blue collars are significantly larger than the estimated coefficients for clerical workers, intermediate professions and managers/high-skill workers at 0.1% ($p = 0.0000$ for all the comparisons).

Table 15. Impact of group-affiliated firm closures on ILM flows from closing BG firms in different EPL regimes

	[40-60]				[45-55]				[35-65]			
	Size at 0		Size at -2		Size at 0		Size at -2		Size at 0		Size at -2	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Time from shock	Below 50	Above 50	Below 50	Above 50	Below 50	Above 50	Below 50	Above 50	Below 50	Above 50	Below 50	Above 50
-4	0.01230	0.03901	-0.00971	-0.01007	0.02618	0.09653	-0.01392	-0.01377	-0.00712	0.01961	-0.00819	-0.01417
	(0.03144)	(0.03134)	(0.02231)	(0.02291)	(0.05084)	(0.05477)	(0.02786)	(0.02812)	(0.02428)	(0.02408)	(0.01813)	(0.01956)
-3	0.01249	0.02181	-0.00294	-0.01077	0.00989	0.02822	0.00995	0.00073	0.01163	0.00452	0.00001	-0.01168
	(0.02025)	(0.01956)	(0.01491)	(0.01508)	(0.03105)	(0.03415)	(0.01836)	(0.01773)	(0.01676)	(0.01608)	(0.01238)	(0.01238)
-2	-	-	-	-	-	-	-	-	-	-	-	-
	(-)	(-)	(-)	(-)	(-)	(-)	(-)	(-)	(-)	(-)	(-)	(-)
-1	0.04609*	0.11819***	0.10355***	0.15595***	0.05134	0.11505**	0.09323***	0.15331***	0.05110**	0.10246***	0.12818***	0.14514***
	(0.02054)	(0.02349)	(0.01749)	(0.02449)	(0.03309)	(0.03523)	(0.02275)	(0.02779)	(0.01717)	(0.02096)	(0.01458)	(0.02090)
0	0.19364***	0.22580***	0.25529***	0.23343***	0.16630**	0.19805**	0.23864***	0.21254***	0.20015***	0.19532***	0.26899***	0.22611***
	(0.03378)	(0.04023)	(0.02716)	(0.03305)	(0.05625)	(0.06205)	(0.03501)	(0.03744)	(0.02769)	(0.03655)	(0.02208)	(0.02845)
Pair FE	Yes		Yes		Yes		Yes		Yes		Yes	
N	88852		164600		44372		95256		144665		234624	

Note: The table reports the coefficients $\widehat{\delta}^{Int}_{\tau} - \widehat{\delta}^{Int}_{-2}$ estimated in equation (7) in which which distinguish flows that originate from firms below 50 employees and flows from firms above 50. The flows are measured as the ratio of workers moving from closing BG-affiliated firm j to firm k in year t, to the total number of workers displaced by firm j in year t. Event date 0 is the last year of activity of the closing firm. The first panel focuses on firms in the 40-60 employee bucket; the second panel on firms in the 45-55 employee bucket; the third panel on firms in the 35-65 employee bucket. We include firm-pair fixed effects and year dummies in our specification. Standard errors in parenthesis are clustered at the group level. Significance levels are * 5%, ** 1%, *** 0.1%. In the first panel, at $\tau = -1$, the coefficient $\widehat{\delta}^{Int}_{\tau} - \widehat{\delta}^{Int}_{-2}$ for firms above 50 (column (1)) is significantly larger than the coefficient for firm below 50 (column (2)) at 0.1% ($p = 0.006$) when we assign firms to treatment using size at $\tau = 0$; it is significantly larger at 5% ($p = 0.0364$) when we assign firms to treatment using size at $\tau = -2$ (columns (3) and (4)). In the second panel, at $\tau = -1$ the coefficient $\widehat{\delta}^{Int}_{\tau} - \widehat{\delta}^{Int}_{-2}$ for firms above 50 is significantly larger than the coefficient for firm below 50 at 10% ($p = 0.085$) when we assign firms to treatment using size at $\tau = 0$ (columns (5) and (6)), and it is at 5% ($p = 0.048$) when we assign firms to treatment using size at $\tau = -2$ (columns (7) and (8)). In the third panel, at $\tau = -1$ the coefficient $\widehat{\delta}^{Int}_{\tau} - \widehat{\delta}^{Int}_{-2}$ for firms above 50 is significantly larger than the coefficient for firm below 50 at 5% ($p = 0.019$) when we assign firms to treatment using size at $\tau = 0$ (columns (9) and (10)); the difference is not significant when we rely on size at $\tau = -2$. At $\tau = 0$ the coefficients are not significantly different.

Table 16. Impact of group-affiliated firm closures on ILM flows, by firm of destination characteristics

	VA per worker		Capex	
	(1)	(2)	(3)	(4)
Distance from the shock	Below Median	Above Median	Below Median	Above Median
-4	-0.00671	-0.00307	-0.00150	-0.00408
	(0.00969)	(0.00802)	(0.01282)	(0.00782)
-3	-0.00926	0.00149	0.00077	-0.00227
	(0.00683)	(0.00567)	(0.01021)	(0.00533)
-2	-	-	-	-
	(-)	(-)	(-)	(-)
-1	0.09424***	0.14294***	0.07021***	0.13731***
	(0.00875)	(0.00873)	(0.01103)	(0.00803)
0	0.22027***	0.24178***	0.21007***	0.23634***
	(0.01436)	(0.01328)	(0.01622)	(0.01278)
PairFE	Yes		Yes	
N	1588976		1592904	

Note: The table reports the effects of BG firms closures on firm-to-firm worker flows from closing BG firms to ILM destination firms with: Value Added Per Worker below/above median (columns (1)-(2)); Capex (capital expenditures) below/above median (columns (3)-(4)). All destination-firm characteristics are measured taking the average over the period $\tau \in [-4, -2]$. The flows are measured as the ratio of workers moving from closing BG-affiliated firm j to firm k in year t, to the total number of workers displaced by firm j in year t. Event date 0 is the last year of activity of the closing firm. The figure plots the change in bilateral worker flows from event date -2 to event date $\tau \in [-4, 0]$, relative to the counterfactual flows. We include firm-pair fixed effects and year dummies in our specification. Standard errors in parenthesis are clustered at the group level. Significance levels are * 5%, ** 1%, *** 0.1%. At $\tau = -1$ ILM flows to firms with high VA per Worker are significantly higher than ILM flows to firms with low VA per Worker; the difference being positive and 0.1% significant at $\tau = -1$ ($p = 0.0000$). ILM flows to high Capex firms are significantly higher than ILM flows to low Capex firms: the difference is positive and 0.1% significant at $\tau = -1$ ($p = 0.0000$). Differences between flows are not significant at $\tau = 0$ ($p = 0.14$ for firms with Value Added Per Worker above/below median and $p = 0.13$ for firms with Capex above/below median.

Table 17. Flows to unemployment around firm closures, BG firms versus stand-alone firms

	(1)	(2)
Distance from the shock	Flows from Stand-Alone firms	Flows from BG-affiliated firms
-4	-0.00006	-0.00664
	(0.00279)	(0.00761)
-3	-0.00211	-0.00085
	(0.00162)	(0.00419)
-2	-	-
	(-)	(-)
-1	0.08261***	0.04759***
	(0.00160)	(0.00417)
0	0.05070***	0.04330***
	(0.00270)	(0.00744)
Firm FE	Yes	
N	1336673	

Note: The table reports the coefficients estimated from equation (8) in which we distinguish worker flows to unemployment that originate from stand-alone firms and flows to unemployment that originate from group-affiliated firms. Flows to unemployment are measured as number of workers moving to unemployment normalized by the size of the firm's workforce. The estimated coefficients measure changes in worker flows to unemployment from event date -2 to event dates $\tau \in [-4, 0]$, relative to the counterfactual flows. $\tau = 0$ is the last year of activity of the closing firm. We include firm fixed effects and year dummies in our specification. Standard errors in parenthesis are clustered at the group level for BG firms and at the firm level for stand-alone firms. Significance levels are * 5%, ** 1%, *** 0.1%. The difference between the coefficients of flows from SA firms and flows from BG firms is positive and significant at 0.1% ($p = 0.0000$) at $\tau = -1$, while it is not significant at $\tau = 0$.

Table 18. Flows to unemployment around firm closures, BG firms versus stand-alone firms, by occupation

	Blue collars		Clerical Support		Intermediate		Managers	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Distance from the shock	Stand-Alone	BG-affiliated	Stand-Alone	BG-affiliated	Stand-Alone	BG-affiliated	Stand-Alone	BG-affiliated
-4	0.00126	-0.00263	-0.00066	-0.00244	0.00018	0.00114	-0.00084	-0.00271
	(0.00095)	(0.00211)	(0.00102)	(0.00212)	(0.00074)	(0.00216)	(0.00070)	(0.00203)
-3	-0.00017	-0.00106	-0.00231**	0.00150	0.00044	-0.00104	-0.00007	0.00024
	(0.00070)	(0.00144)	(0.00076)	(0.00134)	(0.00046)	(0.00126)	(0.00040)	(0.00124)
-2	-	-	-	-	-	-	-	-
	(-)	(-)	(-)	(-)	(-)	(-)	(-)	(-)
-1	0.03100***	0.01799***	0.03754***	0.01444***	0.00923***	0.00879***	0.00484***	0.00637***
	(0.00070)	(0.00143)	(0.00076)	(0.00142)	(0.00045)	(0.00123)	(0.00039)	(0.00114)
0	0.02381***	0.01815***	0.01596***	0.01000***	0.00629***	0.00562**	0.00463***	0.00953***
	(0.00090)	(0.00215)	(0.00090)	(0.00206)	(0.00071)	(0.00196)	(0.00067)	(0.00195)
Firm × Occupation FE	Yes		Yes		Yes		Yes	
N	4549832							

Note: The table reports the coefficients of unemployment flows originating from SA firms and unemployment flows from BG firms jointly estimated in a single specification in which we distinguish flows within four occupational categories: blue collars, clerical workers, intermediate professions, managers/high-skill workers. The specification also includes firm-pair×occupation fixed effects and year dummies. Flows to unemployment are measured as number of workers moving to unemployment normalized by the size of the firm's workforce. The estimated coefficients measure the changes in worker flows to unemployment from event date -2 to event dates $\tau \in [-4, 0]$, relative to the counterfactual flows. $\tau = 0$ is the last year of activity of the closing firm. Columns (1)-(2) shows results for blue collar workers. Columns (3)-(4) shows results for clerical workers. Columns (5)-(6) shows results for intermediate professionals. Columns (7)-(8) shows results for managers and high-skill workers. Standard errors in parenthesis are clustered at the group level for BG firms and at the firm level for stand-alone firms. Significance levels are * 5%, ** 1%, *** 0.1%. For blue collar workers the difference between the estimated coefficient of flows from SA firms and the coefficient of flows from BG firms is positive and significant at 0.1% ($p = 0.0000$)at $\tau = -1$, and at 5% ($p = 0.015$)at $\tau = 0$. For clerical workers the difference is positive and significant at 0.1% ($p = 0.0000$)at $\tau = -1$, and at 1% ($p = 0.008$) at $\tau = 0$.

Table 19. Wage changes: closures vs. normal times by occupational categories

	Change in Hours Worked		**Hourly Wage Change**		**Annual Wage Change**	
	Origin	Pair	Origin	Pair	Origin	Pair
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Destination firm group affiliated	0.0904***	0.0483	0.0426***	0.0295	0.1357***	0.0724
	(0.018)	(0.055)	(0.006)	(0.032)	(0.018)	(0.055)
Same Group	0.1667***	0.0482	0.0174	-0.0157	0.1873***	0.0374
	(0.033)	(0.046)	(0.017)	(0.028)	(0.035)	(0.054)
Closure × destination firm group affiliated	-0.0008	0.0353	-0.0123	-0.0142	-0.0136	0.0229
	(0.024)	(0.053)	(0.008)	(0.031)	(0.025)	(0.054)
Closure × Same Group	-0.0962*	-0.1005*	0.0160	-0.0079	-0.0806	-0.1104*
	(0.043)	(0.044)	(0.019)	(0.026)	(0.045)	(0.051)
Male	0.0391***	0.0240***	0.0040**	0.0006	0.0437***	0.0246***
	(0.004)	(0.003)	(0.001)	(0.002)	(0.004)	(0.003)
Age	0.0438***	0.0304***	-0.0013	-0.0064***	0.0420***	0.0239***
	(0.003)	(0.002)	(0.001)	(0.001)	(0.003)	(0.002)
Age squared	-0.0005***	-0.0004***	0.0000	0.0001***	-0.0005***	-0.0003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Duration	-0.0045***	-0.0039***	0.0003***	0.0003***	-0.0042***	-0.0036***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Same Group × Managers	-0.0985*	0.0045	0.1079***	0.0491	0.0157	0.0629
	(0.049)	(0.044)	(0.026)	(0.038)	(0.050)	(0.053)
Same Group × Intermediate Occupations	-0.0214	0.0934	0.0370*	0.0142	0.0086	0.1085
	(0.044)	(0.062)	(0.018)	(0.024)	(0.046)	(0.065)
Same Group × Clerical Support	-0.0364	-0.0104	0.0091	0.0216	-0.0261	0.0109
	(0.057)	(0.067)	(0.022)	(0.029)	(0.062)	(0.070)
Closure × Same Group × Managers	0.0830	0.0141	-0.0840**	-0.0330	-0.0092	-0.0280
	(0.051)	(0.044)	(0.028)	(0.039)	(0.051)	(0.053)
Closure × Same Group × Intermediate Occupations	-0.0098	-0.0888	-0.0262	0.0019	-0.0280	-0.0873
	(0.046)	(0.063)	(0.019)	(0.025)	(0.048)	(0.065)
Closure × Same Group × Clerical Support	0.0415	-0.0047	-0.0238	-0.0175	0.0187	-0.0211
	(0.069)	(0.068)	(0.025)	(0.031)	(0.071)	(0.071)
N	905,089	905,089	905,087	905,087	909,556	909,556
Firm of origin FE	YES	NO	YES	NO	YES	NO
Firm of origin × destination firm FE	NO	YES	NO	YES	NO	YES
Year indicators	YES	YES	YES	YES	YES	YES
Time to closure indicators	YES	YES	YES	YES	YES	YES

Note: In columns (1)-(2) the dependent variable is the percentage change in the number of hours worked of a worker transiting from affiliated firm j to firm k in year t. In columns (3)-(4) the dependent variable is the percentage change in the hourly wage of a worker transiting from affiliated firm j to firm k in year t. In columns (5)-(6) the dependent variable is the percentage change in the annual wage of a worker transiting from affiliated firm j to firm k in year t. *Destination firm group affiliated* is an indicator equal to 1 if firm k is group affiliated. *Same Group* is an indicator equal to 1 if firm j and firm k belong to the same group. *Closure* is an indicator equal to 1 in the last two years of firm j's activity ($\tau = -1$ and $\tau = 0$). *Duration* measures the number of days spent by the worker in the firm of origin in the year before the job move. All relevant second and third level interactions are included. 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. Standard errors are clustered at the firm of origin level.

A Appendix

A.1 A simple model of ILM activity

In this section we lay out a simple model to study the optimal labor adjustment response to a (permanent) shock in a business group and in a stand-alone firm. The model allows us to study how the group's adjustment differs from that of a stand-alone, what triggers the use of the ILM in the group, and how the ILM creates value. We will focus here on the case where only one firm in the group is hit by a shock, while the other affiliated firm is not.

We describe here the production technology. Each firm produces using labor only, and output is given by

$$Y_i = \theta_i f_i(L_i) \tag{9}$$

where θ_i is a parameter capturing total factor productivity, and the function f satisfies $f' > 0$, $f'' < 0$. Without loss of generality we also assume that $\lim_{L \to 0} f'(L) \to \infty$.[59] There is perfect competition both in the product and in the input markets; the price for the firm's product is $p = 1$ and the wage is w. We denote firm i's stock of labor at the beginning of the period as L_{0i}. In what follows we will omit the subscript i when referring to the stand-alone firm, while denoting with $i = A, B$ the two firms affiliated with the business group.

A.1.1 Labor adjustment in the stand-alone firm

Following the realization of a shock, the firm's total factor productivity is: $\theta' = \theta + \varepsilon$, with $\varepsilon \in (-\infty, +\infty)$. The firm can adjust its labor force by an amount e, and in doing so it faces firing and hiring costs in the external labor market. We assume that adjustment costs are linear, but our results generalize to the case of non-linear adjustment costs: $C(e) = He$ if $e > 0$ and $C(e) = Fe$ if $e < 0$. We also assume, without loss of generality, that the initial stock of labor L_0 satisfies $\theta f'(L_0) \in (w - F, w + H)$. The following Lemma shows that in this second best environment the optimal adjustment policy consists of not adjusting unless the shock is large. In other words, the presence of labor market frictions makes the firm's labor demand less flexible.

Lemma 1. *The stand-alone firm hires workers when the shock is positive and large, fires workers when the shock is negative and large, and does not adjust for moderate realizations of the shock (inaction corridor):*

$$\begin{aligned}
&e^* > 0 \quad s.t.(\theta + \varepsilon) f'(L_0 + e^*) = w + H && if \quad \varepsilon > \varepsilon^H \\
&e^* = 0 && if \quad \varepsilon \in [\varepsilon^L, \varepsilon^H] \\
&e^* < 0 \quad s.t.(\theta + \varepsilon) f'(L_0 + e^*) = w - F && if \quad \varepsilon < \varepsilon^L
\end{aligned}$$

$\varepsilon^H > 0$ *is such that* $(\theta + \varepsilon^H) f'(L_0) = w + H$ *and* $\varepsilon^L < 0$ *is such that* $(\theta + \varepsilon^L) f'(L_0) = w - F$.

A.1.2 Labor adjustment in a business group

Consider now a group composed of two units with production function $Y_i = \theta_i f_i(L_i)$ and $i = A, B$. The group's headquarters has control over labor adjustment decisions in each of the group's units. Suppose that unit A is hit by a shock $\varepsilon \in (-\infty, +\infty)$, hence $\theta'_A = \theta_A + \varepsilon$, while unit B is not, hence its productivity is unchanged and equal to θ_B. Following the shock, the group can adjust unit A's labor force using the external labor market (ELM), but also rely on the internal labor market (ILM), moving workers across units. ILM adjustments are less costly than external ones (we discuss this hypothesis at length in Section 2): for simplicity, we assume here that internal adjustments are costless. We denote with e_i the external labor market adjustment and with i the internal labor

[59] This assumption simplifies the analysis by allowing us to disregard corner solutions without altering the qualitative results.

market flow. We adopt the convention that $i > 0$ when workers are reallocated from unit B to unit A, and $i < 0$ when the flow has the opposite direction. Without loss of generality, we assume that $\theta_A f'_A(L_{0A}) = \theta_B f'_B(L_{0B}) = \theta f'(L_0) \in (w - F, w + H)$,[60] and that $\theta_B f'_B(L_{0A} + L_{0B}) < w - F$.[61]

The headquarters choose e_A, e_B and i so as to maximize the total value of the group:

$$\begin{aligned} \max_{e_A, e_B, i} & [(\theta_A + \varepsilon) f_A(L_{0A} + e_A + i) - w(L_{0A} + e_A + i) - C(e_A) \\ & + \theta_B f_B(L_{0B} + e_B - i) - w(L_{0B} + e_B - i) - C(e_B)] \\ & s.t.\ e_A + i \geq -L_{0A}\ ,\ e_B - i \geq -L_{0B} \end{aligned}$$

The first order conditions of the above problem are:

$$\frac{\partial V}{\partial e_A} = \begin{cases} (\theta_A + \varepsilon) f'_A(L_{0A} + e^*_A + i^*) = w + H & \text{if } e^*_A > 0 \\ (\theta_A + \varepsilon) f'_A(L_{0A} + e^*_A + i^*) \in [w - F, w + H] & \text{if } e^*_A = 0 \\ (\theta_A + \varepsilon) f'_A(L_{0A} + e^*_A + i^*) = w - F & \text{if } e^*_A < 0 \end{cases} \tag{10a}$$

$$\frac{\partial V}{\partial i} = (\theta_A + \varepsilon) f'_A(L_{0A} + e^*_A + i^*) - \theta_B f'_B(L_{0B} + e^*_B - i^*) = 0 \tag{10b}$$

$$\frac{\partial V}{\partial e_B} = \begin{cases} \theta_B f'_B(L_{0B} + e^*_B - i^*) = w + H & \text{if } e^*_B > 0 \\ \theta_B f'_B(L_{0B} + e^*_B - i^*) \in [w - F, w + H] & \text{if } e^*_B = 0 \\ \theta_B f'_B(L_{0B} + e^*_B - i^*) = w - F & \text{if } e^*_B < 0. \end{cases} \tag{10c}$$

The following Proposition shows that when group unit A is hit by a shock while B is not, the size and the mode of the adjustment in unit A depend on the magnitude and the sign of the shock. When the shock is moderate, the group only relies on the ILM to adjust A's labor force. After a large enough positive (negative) shock, the group combines external hiring (firing) in the affected unit with ILM flows to (from) the unit.

Proposition 1. *The optimal adjustment policy in the group entails $e^*_B = 0$ for any ε. There exist two thresholds for ε, $\overline{\varepsilon}$ and $\underline{\varepsilon}$, such that:*

$$\begin{array}{lll} e^*_A > 0,\ i^* > 0, & s.t. (\theta_A + \varepsilon) f'_A(L_{0A} + e^*_A + i^*) = \theta_B f'_B(L_{0B} - i^*) = w + H & if\ \ \varepsilon > \overline{\varepsilon} > 0 \\ e^*_A = 0,\ i^* = \widehat{i}, & s.t. (\theta_A + \varepsilon) f'_A(L_{0A} + i^*) = \theta_B f'_B(L_{0B} - i^*) \in [w - F, w + H] & if\ \ \varepsilon \in [\underline{\varepsilon}, \overline{\varepsilon}] \\ e^*_A < 0,\ i^* < 0, & s.t. (\theta_A + \varepsilon) f'_A(L_{0A} + e^*_A + i^*) = \theta_B f'_B(L_{0B} - i^*) = w - F & if\ \ \varepsilon < \underline{\varepsilon} < 0 \end{array}$$

Proof. Define as $\widehat{i}(\varepsilon)$ the ILM flow that equalizes marginal productivities across the two units absent external adjustments: $(\theta_A + \varepsilon) f'_A(L_{0A} + \widehat{i}(\varepsilon)) = \theta_B f'_B(L_{0B} - \widehat{i}(\varepsilon))$. From concavity of the production functions, $\theta_A f'_A(L_{0A}) = \theta_B f'_B(L_{0B})$ and $\lim_{L_i \to 0} f'_i(L_i) \to \infty$ it follows that $\widehat{i}(\varepsilon)$ exists, it is unique and strictly increasing in ε, and it is positive if (and only if) $\varepsilon > 0$. Moreover, $\theta_A f'_A(L_{0A}) = \theta_B f'_B(L_{0B}) < w + H$ and $\lim_{L_B \to 0} f'_B(L_B) \to \infty$ imply that there exists a threshold level of the shock $\overline{\varepsilon} > 0$, such that when $\varepsilon = \overline{\varepsilon}$, it is: $\theta_B f'_B(L_{0B} - \widehat{i}(\overline{\varepsilon})) = (\theta_A + \overline{\varepsilon}) f'_A(L_0 + \widehat{i}(\overline{\varepsilon})) = w + H$ with $\widehat{i}(\overline{\varepsilon}) > 0$. (See also Figure A1.) For that positive realization of the shock the ILM reallocation from

[60] If one relaxes this assumption, similar qualitative results obtain by re-scaling the threshold levels of the shock in the main Proposition. Also, allowing the marginal productivity of labor to be smaller than $w - F$ (larger than $w + H$) would entail an additional case where unit B optimally reduces (increases) its workforce at the same time as A, hence both units adjust using the external labor market only.

[61] This assumption ensures that when A is hit by a sufficiently large shock, it is not optimal to fully adjust its workforce via the ILM, hence the group must combine ILM reallocations with external firing. Formally, this means that the threshold $\underline{\varepsilon}$ always exists (see below).

unit B to A equalizes marginal productivities across the two units and to $w+H$. In this case it is optimal not to hire from the external labor market. When $\varepsilon > \overline{\varepsilon}$, $\widehat{i}(\varepsilon) > \widehat{i}(\overline{\varepsilon})$ and the internal reallocation that equalizes marginal productivities without external adjustments would make such marginal productivities larger than $w+H$. Then, the FOCs can only be satisfied if external hiring is combined with ILM activity. Indeed, under the assumptions that firing/hiring costs are linear and that internal reallocations are costless, multiple solutions exist in which different amounts of internal flows are combined with external hiring in both units. The introduction of a small cost of internal reallocation would pin down as the unique solution the one indicated above, where $i^* < \widehat{i}(\varepsilon)$ and only the positively shocked unit hires on the external market. Similarly, $\theta_A f_A'(L_{0A}) = \theta_B f_B'(L_{0B}) > w-F$ and $\theta_B f_B'(L_{0B}+L_{0A}) < w-F$ implies that there exists a threshold level of the shock, $\underline{\varepsilon} < 0$, such that when $\varepsilon = \underline{\varepsilon}$, it is: $\theta_B f_B'(L_{0B} - \widehat{i}(\underline{\varepsilon})) = (\theta_A + \underline{\varepsilon}) f_A'(L_0 + \widehat{i}(\underline{\varepsilon})) = w - F$ with $\widehat{i}(\underline{\varepsilon}) < 0$. For that negative realization of the shock the ILM reallocation from unit A to B equalizes marginal productivities across the two units and to $w-F$. In this case it is optimal not to hire from the external labor market. When $\varepsilon < \underline{\varepsilon}$, $\widehat{i}(\varepsilon) < \widehat{i}(\underline{\varepsilon})$ and the internal reallocation that equalizes marginal productivities without external adjustments makes such marginal productivities smaller than $w-F$. Then, the FOCs can only be satisfied if external firing is combined with ILM activity. The same caveat concerning multiplicity of optimal allocations also applies; with a small ILM reallocation cost, the unique solution is such that $|i^*| < |\widehat{i}(\varepsilon)|$ and only the negatively affected unit fires workers. □

A.1.3 ILM response to an adverse shock and firing costs

The following result describes how the magnitude of firing costs determines the ILM flows following an adverse shock. It underpins our prediction that the ILM response to negative shocks is larger when employment protection regulations are stricter, which we test in Section 5.1.

Corollary 1. *Following an adverse shock, the flow of workers reallocated from unit A to the rest of the group is (weakly) increasing in the unit firing cost F. In particular, for any shock $\varepsilon < 0$ there exists a cutoff $\underline{F}$ such that the proportion of workers reallocated through the ILM over the total outflow of workers from firm A is strictly increasing in F for $F < \underline{F}$ and equal to 1 if $F \geq \underline{F}$.*

Proof. From the concavity of production functions, and $\theta_B f_B'(L_{0B} - \widehat{i}(\underline{\varepsilon})) = (\theta_A + \underline{\varepsilon}) f_A'(L_0 + \widehat{i}(\underline{\varepsilon})) = w - F$, it follows that $\underline{\varepsilon}$ is strictly decreasing in F. This in turn implies that, for any shock ε, there exists a unique threshold value $\underline{F}(\varepsilon)$ that defines two regions.

First, when $F < \underline{F}$ it is $\varepsilon < \underline{\varepsilon}$, hence by Proposition 1, i^* and e_A^* are defined by $(\theta_A + \varepsilon) f_A'(L_{0A} + e_A^* + i^*) = \theta_B f_B'(L_{0B} - i^*) = w - F$. Applying the implicit function theorem, one obtains $\partial i^*/\partial F = 1/(\theta_B f'') < 0$, $\partial e_A^*/\partial F = -1/((\theta_A + \varepsilon) f'') > 0$, and $\partial(\frac{i^*}{i^* + e_A^*})/\partial F > 0$.

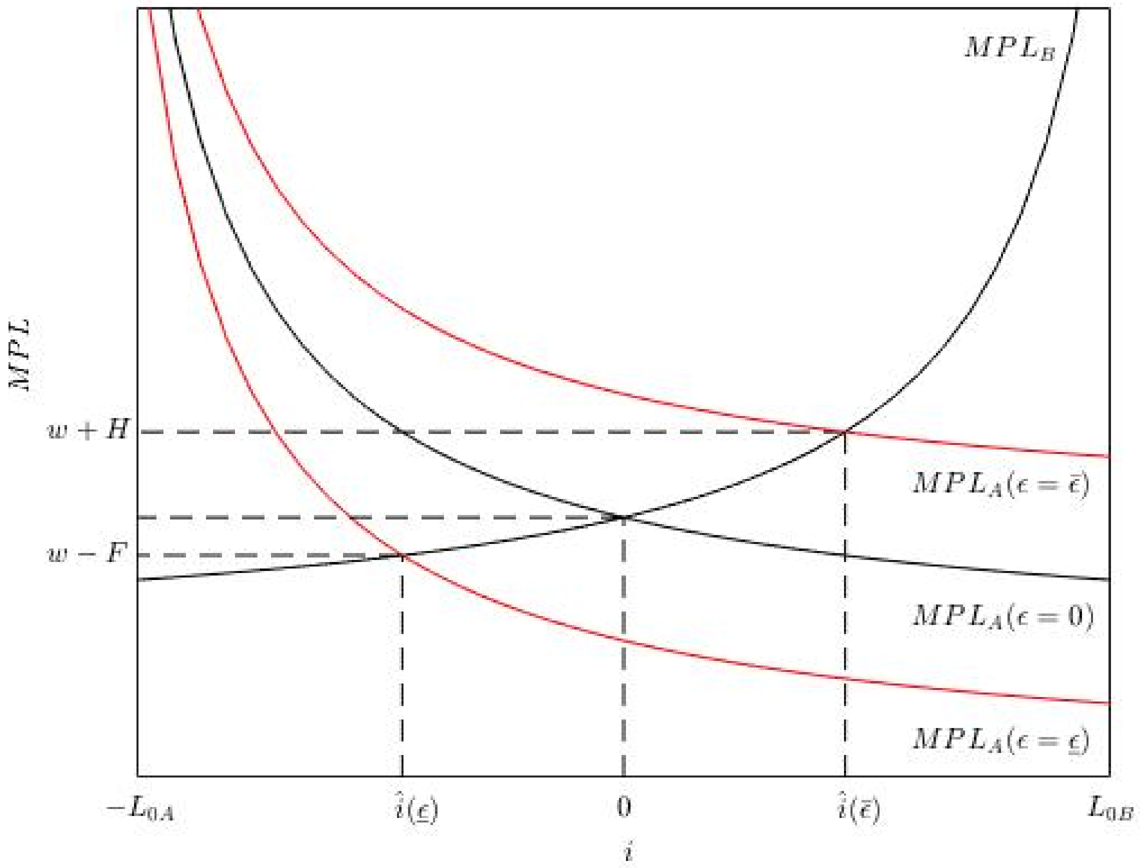
Second, when $F \geq \underline{F}$, it is $\varepsilon \geq \underline{\varepsilon}$, hence by Proposition 1, $e_A^* = 0$ and $i^* = \widehat{i}$ is defined by $(\theta_A + \varepsilon) f_A'(L_{0A} + i^*) = \theta_B f_B'(L_{0B} - i^*) \in [w - F, w + H]$. Therefore, the size of the ILM flow from A to B is independent of F and the fraction $\frac{i^*}{i^* + e_A^*}$ is constant and equal to 1. □

A.1.4 Value creation through the ILM

To understand how the ILM creates value, we compare here the optimal labor adjustment response of a group composed of units A and B with that of two identical, but not affiliated, firms. To this purpose, it is useful to compare the threshold levels of the shock that characterize the group's optimal adjustment policy with those of a stand-alone firm identical to unit A (i.e. $\theta_A = \theta$, $f_A = f$ and $L_{0A} = L_0$). The stand-alone firm identical to unit B is not hit by a shock and, by the assumption $\theta_B f_B'(L_{0B}) \in (w - F, w + H)$, it does not adjust.

Corollary 2. *The threshold levels of the shock for the stand-alone firm and for the group are such that: $\overline{\varepsilon} > \varepsilon^H > 0$ and $\underline{\varepsilon} < \varepsilon^L < 0$.*

Figure A1: Graphic Representation of Proposition 1's proof. The horizontal axis measures the ILM flow from unit B to unit A, the vertical axis displays the marginal productivity of labor of the two units (MPL_A, MPL_B). The optimal ILM response to a productivity shock of size ε hitting unit A is found by identifying the intersection between MPL_B and the relevant MPL_A. All MPL_A curves above (below) the black one correspond to positive (negative) shocks.



Proof. The threshold level $\bar{\varepsilon} > 0$ is such that $(\theta_A + \bar{\varepsilon})f'(L_{0A} + \widehat{i}(\bar{\varepsilon})) = w + H$, whereas $\varepsilon^H > 0$ is such that $(\theta + \varepsilon^H)f'(L_0) = w + H$. Since $\widehat{i}(\bar{\varepsilon}) > 0$ (in the ILM workers flow towards the positively affected unit (Unit A)), then $f'(L_{0A} + \widehat{i}(\bar{\varepsilon})) < f'(L_0)$. This implies that $\bar{\varepsilon} > \varepsilon^H > 0$. Similarly, the threshold level $\underline{\varepsilon} < 0$ is such that $(\theta_A + \underline{\varepsilon})f'(L_{0A} + \widehat{i}(\underline{\varepsilon})) = w - F$, whereas $\varepsilon^L < 0$ is such that $(\theta + \varepsilon^L)f'(L_0) = w - F$. Since $\widehat{i}(\underline{\varepsilon}) < 0$, i.e. the ILM makes workers flow away from the adversely affected unit, then $f'(L_0 + \widehat{i}(\underline{\varepsilon})) > f'(L_0)$. This implies that $\underline{\varepsilon} < \varepsilon^L < 0$. □

This result allows us to identify three regions. First, when the shock is small (i.e. $\varepsilon \in [\varepsilon^L, \varepsilon^H]$), the presence of hiring/firing costs in the external market induces the stand-alone firm not to adjust, whereas the group adjusts its labor force using the ILM. The availability of a cheaper internal channel allows the group to reallocate its labor force towards more productive uses, thereby increasing value by removing differences in the marginal productivities of labor across the two units.

Second, for intermediate levels of the shock (i.e. either $\varepsilon \in [\varepsilon^H, \bar{\varepsilon}]$) or $\varepsilon \in [\underline{\varepsilon}, \varepsilon^L]$), the stand-alone firm A adjusts on the external market, stand-alone firm B does not adjust, while the group unit relies uniquely on the ILM. The use of the ILM increases the group value not only because it allows the group to save on the external adjustment cost born by stand-alone firm A and to improve the allocation of labor across the two units, but also because it allows the group to adjust in unit A more than in the identical stand-alone firm. The intuition is that the stand-alone adjusts until it reaches the level of employment such that the marginal productivity is equal to either $w - F$ or $w + H$. Instead unit A adjusts more because it uses a cheaper channel and there is scope for increasing the group value by reducing further the difference between the marginal productivities across the two units.

Finally, for large values of the shock (i.e. either $\varepsilon > \overline{\varepsilon}$ or $\varepsilon < \underline{\varepsilon}$), the total adjustment in unit A is the same as in the stand-alone ($i^* + e_A^* = e^*$). However, the use of the ILM increases value because it allows the group to improve the allocation of labor across the two units and to avoid firing/hiring costs in unit A.

The above result highlights two different channels through which the ability to operate an ILM creates value: *(i) Flexibility:* The ILM allows affiliated firms to adjust their labor force more than stand-alones and to take advantage of a more efficient allocation of labor across the affiliated units; *(ii) Lower adjustment costs:* The ILM allows affiliated firms to bear lower firing and hiring costs. This effect is evident in the region where the stand-alone and the affiliated firm perform the same level of total adjustment, yet the affiliated firm relies in part on the cheaper internal channel. Evidently, while the ILM allows to bypass firing (or hiring) costs, some inefficiency is borne by unit B in the organization, that may end up employing an amount of workers larger (or smaller) than individually optimal, i.e. such that the marginal productivity of labor is smaller (larger) than w. It is however worth emphasizing that the optimal ILM allocation ensures that the efficiency loss in unit B is more than offset by the gain in unit A. Hence, the value of a group with an ILM is larger than the value of a set of identical stand-alone companies.[62]

[62] Note that although for brevity we studied here the optimal response to a shock hitting only one unit in the organization, our simple analysis points to the coinsurance value of ILMs; in a more general model where both group units are exposed to idiosyncratic shocks ex-ante, the ILM would create value in all states of nature where only one unit is hit by a shock, and a fortiori in states of nature where two units are hit by shocks of opposite sign.

A.2 Professional categories in the DADS

Table A1. Professional categories in the DADS

CODE	CATEGORY
10	Farmers
2	**CEOs and business owners**
21	CEOs and business owners of artisan firms with less than 10 employees
22	CEOs and business owners of sales/service firms with less than 10 employees
23	CEOs of firms with more than 10 employees
3	**Managers and professionals; engineers**
31	Doctors, lawyers, accountants and other professionals
33	Managers in the Public Administration
34	Professors, researchers, scientific occupations
35	Journalists and media/arts/entertainment superior occupations
37	Administrative/commercial managers
38	Engineers and technical managers
4	**Intermediate occupations**
42	Teachers, librarians and other occupations in education
43	Healthcare (e.g. nurses, midwives) 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 (e.g. programmers, lab technicians, land surveyors)
48	Foremen
5	**Clerical support, sales and service occupations**
52	Clerical support in the Public Administration
53	Surveillance and security
54	Clerical support
55	Sales and related occupations
56	Personal service and personal care workers
6	**Blue collar occupations**
62	Industrial skilled workers
63	Artisan skilled workers
64	Drivers
65	Maintenance, repair and transport skilled workers
67	Industrial non skilled workers
68	Artisan non skilled workers
69	Agricultural workers

Source: INSEE.

A.3 Descriptive evidence on ILMs: Excess probabilities

This Appendix describes the methodology used to estimate equation (1).

A.3.1 Methodology

The parameter $\gamma_{c,j,t}$ measures ILM activity for each set c of job movers $\times$ group-affiliated firm of destination $\times$ year. Such a measure is identified only for BG-affiliated firms of destination (because the variable $BG_{i,k,j,t}$ has no variation in the case of non BG-affiliated firms), but the estimation sample of course includes workers who move from any (BG- and non BG-affiliated) firm to any (BG- and non BG-affiliated) firm.

Direct estimation of equation (1) would require a data set with one observation for each combination of firm-to-firm mover and group-affiliated firm for each year. As our data set contains about 1,574,000 firm-to-firm transitions and approximately 40,000 group-affiliated firms per year, direct estimation of the model would require the construction of a data set with as many as 62 billion observations per year. In order to estimate the parameters of equation (1) while keeping the dimensionality of the problem reasonable, we follow the methodology developed in Kramarz and Thesmar (2013) and Kramarz and Nordström Skans (2014). We define:

$$R^{BG}_{c,j,t} \equiv \frac{\sum_{i\in c,k} E_{i,c,k,j,t} BG_{i,k,j,t}}{\sum_{i\in c,k} BG_{i,k,j,t}} = \beta_{c,j,t} + \gamma_{c,j,t} + \widetilde{u}^{BG}_{c,j,t} \tag{11}$$

where $R^{BG}_{c,j,t}$ is the fraction of job movers that, in year t, find a job in firm j among all firm-to-firm movers in set c whose firm of origin k belongs to the same group as firm j. This fraction might be high because firm j has a high propensity to hire job movers in set c (maybe because c is composed of workers originating from a given location or occupation), and happens to be part of a group intensive in workers belonging to set c. In this case, one observes many job movers in set c hired by firm j and originating from j's group, but this cannot be ascribed to the ILM channel.

We then compute the fraction of workers that find a job in firm j among all firm-to-firm movers in set c whose firm of origin k does *not* belong to the same group as firm j:

$$R^{-BG}_{c,j,t} \equiv \frac{\sum_{i\in c,k} E_{i,c,k,j,t}(1 - BG_{i,k,j,t})}{\sum_{i\in c,k}(1 - BG_{i,k,j,t})} = \beta_{c,j,t} + \widetilde{u}^{-BG}_{c,j,t} \tag{12}$$

Notice that the subscript k disappears since we sum over all firms of origin, hence over all k's. Notice also that summing up the denominators in equations (11) and (12) one obtains the total number of job movers in set c that move from *any* firm in year $t-1$ to *any* firm in year t.

Taking the difference between the two ratios eliminates the job-mover-set $\times$ firm $\times$ year effect $\beta_{c,j,t}$:

$$G_{cj,t} \equiv R^{BG}_{c,j,t} - R^{-BG}_{c,j,t} = \gamma_{c,j,t} + u^{G}_{i,j,t}. \tag{13}$$

We estimate the parameter $\gamma_{c,j,t}$ for each firm $\times$ set c $\times$ year, as the difference between two probabilities: first, the probability that a worker, belonging to the set c and originating from a firm affiliated with the same group as firm j, finds a job in firm j; second, the probability that a worker, belonging to the set c and originating from a firm that is *not* affiliated with the same group as firm j, finds a job in firm j.

Estimation procedure: In order to estimate our parameter of interest, $\gamma_{c,j,t}$, for each firm, year t and each job movers class c, we identify the set of firm-to-firm movers in class c (e.g. workers moving between two given occupations o and z) between year $t-1$ and year t. Then, we associate each class c with a firm j. For each pair $\{c, j\}$, we separate those transitions that originate from the same group as firm j from those transitions that do not. This allows us to compute the denominators of the ratios $R^{BG}_{c,j,t}$ and $R^{-BG}_{c,j,t}$ defined in (11) and (12).[63] For each pair $\{c,j\}$, we then compute the number of firm-to-firm movers in class c that find a job in 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 numerators of the ratios $R^{BG}_{c,j,t}$ and $R^{-BG}_{c,j,t}$ defined in (11) and (12), and ultimately to estimate our parameter of interest $\gamma_{c,j,t}$ for each class-firm combination. Excess probabilities can be computed using alternative definitions of c.

The excess probability $\gamma_{c,j,t}$ we estimate is a measure of ILM activity for each class $c \times$ destination firm $\times$ year. We then aggregate these measures at the firm$\times$year level, taking simple averages of the estimated $\widehat{\gamma}_{c,j,t}$ across different classes.[64] This allows us to estimate, for each group-affiliated firm in our sample, time-varying but firm-specific *average excess probabilities* $\widehat{\gamma}_{j,t}$, that we present in Table 2.

Equivalence result: *The coefficient* $\widehat{\gamma}_{c,j,t}$ *estimated in equation* (13) *is equal to the coefficient obtained from direct estimation of equation* (1).

Proof. The coefficient from the linear probability model in equation (1), estimated on a sample of N individuals, for given set c, and a given firm of destination j, in year t (subscript t dropped), is the standard OLS coefficient:

$$\begin{aligned}
\gamma^{OLS}_{c,j} &= \frac{Cov(E_{i,c,j}, BG_{i,j})}{Var(BG_{i,j})} = \frac{\sum_{i=1}^{N}(E_{i,c,j} - \overline{E}_{c,j})(BG_{i,j} - \overline{BG}_j)/N}{\sum_{i=1}^{N}(BG_{i,j} - \overline{BG}_j)^2/N} \\
&= \frac{\sum_{i=1}^{N} E_{i,c,j}BG_{i,j}/N - \overline{E}_{c,j}\overline{BG}_j}{\sum_{i=1}^{N} BG^2_{i,j}/N - \overline{BG}^2_j} = \frac{\sum_{i=1}^{N} E_{i,c,j}BG_{i,j}/N - \overline{E}_{c,j}\overline{BG}_j}{\overline{BG}_j - \overline{BG}^2_j} \qquad (14)
\end{aligned}$$

where N is the number of workers belonging to the set c.

Since $\beta^{OLS}_{c,j} = \overline{E}_{c,j} - \gamma^{OLS}_{c,j}\overline{BG}_j$, we get:

$$\begin{aligned}
\gamma^{OLS}_{c,j} + \beta^{OLS}_{c,j} &= \frac{\sum_{i=1}^{N} E_{i,c,j}BG_{i,j}/N - \overline{E}_{c,j}\overline{BG}_j}{\overline{BG}_j - \overline{BG}^2_j} + \overline{E}_{c,j} - \gamma^{OLS}_{c,j}\overline{BG}_j \\
&= \frac{\sum_{i=1}^{N} E_{i,c,j}BG_{i,j}/N - \overline{E}_{c,j}\overline{BG}_j + \overline{E}_{c,j}(\overline{BG}_j - \overline{BG}^2_j) - \gamma^{OLS}_{c,j}\overline{BG}_j(\overline{BG}_j - \overline{BG}^2_j)}{\overline{BG}_j - \overline{BG}^2_j} \\
&= \frac{\sum_{i=1}^{N} E_{i,c,j}BG_{i,j}/N - \overline{E}_{c,j}\overline{BG}^2_j - \gamma^{OLS}_{c,j}\overline{BG}_j(\overline{BG}_j - \overline{BG}^2_j)}{\overline{BG}_j - \overline{BG}^2_j} \\
&= \frac{\sum_{i=1}^{N} E_{i,c,j}BG_{i,j}/N - \overline{BG}^2_j(\overline{E}_{c,j} + \gamma^{OLS}_{c,j} - \gamma^{OLS}_{c,j}\overline{BG}_j)}{\overline{BG}_j - \overline{BG}^2_j} \\
&= \frac{\sum_{i=1}^{N} E_{i,c,j}BG_{i,j}/N - \overline{BG}^2_j(\beta^{OLS}_{c,j} + \gamma^{OLS}_{c,j})}{\overline{BG}_j - \overline{BG}^2_j}
\end{aligned}$$

[63] We then drop the pairs in which this distinction cannot be drawn because either all the transitions originate from j's group or all the transitions originate from the external labor market. Trivially, on those sets of workers it is not possible to identify the excess probabilities. This restriction is without loss of identifying variation since the discarded observations are uninformative conditional on the fixed effects.

[64] In unreported results (available upon request) we also take weighted averages, and obtain similar results. The weights reflect the importance of the transitions in set c for the group firm j is affiliated with. In other words, the weight is the ratio of the number of transitions in set c that originate from firm j's group to the total number of transitions (for all the sets associated with firm j) that originate from firm j's group.

Hence,

$$(\overline{BG}_j - \overline{BG}_j^2)(\gamma_{c,j}^{OLS} + \beta_{c,j}^{OLS}) = \sum_{i=1}^{N} E_{i,c,j} BG_{i,j}/N - \overline{BG}_j^2(\beta_{c,j}^{OLS} + \gamma_{c,j}^{OLS}) \tag{15}$$

$$\gamma_{c,j}^{OLS} + \beta_{c,j}^{OLS} = \frac{\sum_{i=1}^{N} E_{i,c,j} BG_{i,j}/N}{\overline{BG}_j} = \frac{\sum_{i=1}^{N} E_{i,c,j} BG_{i,j}}{\sum_{i=1}^{N} BG_{i,j}} \tag{16}$$

as in equation (11). Next, substituting (14) into $\beta_{c,j}^{OLS} = \overline{E}_{c,j} - \gamma_{c,j}^{OLS}\overline{BG}_j$, we get:

$$\begin{aligned}
\beta_{c,j}^{OLS} &= \overline{E}_{c,j} - \frac{\sum_{i=1}^{N} E_{i,c,j} BG_{i,j}/N - \overline{E}_{c,j}\overline{BG}_j}{\overline{BG}_j - \overline{BG}_j^2}\overline{BG}_j \\
&= \frac{\overline{E}_{c,j}(1 - \overline{BG}_j) - \sum_{i=1}^{N} E_{i,c,j} BG_{i,j}/N + \overline{E}_{c,j}\overline{BG}_j}{1 - \overline{BG}_j} \\
&= \frac{\sum_{i=1}^{N} E_{i,c,j}(1 - BG_{i,j})}{\sum_{i=1}^{N} (1 - BG_{i,j})}
\end{aligned}$$

as in equation (12). □

A.3.2 Additional Descriptive Evidence on ILM Activity

ILM activity and diversification – In Table A3 we investigate whether our estimated measures of ILM activity are larger for firms affiliated with more diversified groups. We first average at the firm level the $\widehat{\gamma}_{j,c,t}$ estimated controlling for firm × occupation-pair effects. We then regress $\widehat{\gamma}_{j,t}$ on a number of firm and group characteristics, controlling for firm×group fixed effects to account for unobserved heterogeneity at the firm×group level,[65]and year dummies to control for macroeconomic shocks common to all firms. Group diversification is computed by taking the opposite of an Herfindahl-Hirschman Index based on the employment shares of the group in the different macro/4-digit industries or geographical areas. In sum, columns 1-8 show that diversification both across sectors (macro sectors in columns 1-2 and 4-digit sectors in columns 3-4) and geographical areas (Paris vs non-Paris in columns 5-6, and across regions in columns 7-8) is associated with more intense ILM activity, the more so the larger group.[66] The effect of diversification is sizeable: for example, in a group of average size, a one-standard deviation increase in (4-digit) sectoral diversification (see Appendix Table A2) boosts ILM activity by 0.0081 percentage points, which represents a 8.9% increase in the average excess probability. In a group which is one-standard deviation larger than the average, the increase in ILM activity equals 0.0246 percentage points, which represents as much as 27% of the average excess probability.

[65]Since firms may change the group they are affiliated with, firm effects do not capture the firm×group match-specific unobserved heterogeneity.

[66]Table A3 shows a negative correlation between the number of affiliated firms and the excess probability, in the presence of a group fixed effect. This is explained by the fact that in years when groups lose one or more units due to closures, ILM activity intensifies, hence larger excess probabilities are observed, a result we present in Table B1, Appendix B of Cestone, Fumagalli, Kramarz, and Pica (2016).

Table A2. Descriptive Statistics

	Mean	**St.dev.**	**Min**	**Max**	**N**
$\overline{\gamma}_{jt}$	0.091	0.23	-0.63	1	289,689
Firm size (empl.)	157.83	1468.45	0.005	217640	289,689
(Log) Firm size	3.593	1.481	-5.298	12.291	289,689
Rest of the group size (empl.)	10955	29375.43	0.001	349038	289,689
(Log) Rest of the group size	6.107	2.786	-6.908	12.763	289,689
Number of 4 digit sectors	11.52	18.57	1	92	289,689
Number of macrosectors	1.88	0.99	1	6	289,689
Number of regions	5.4	6.45	1	22	289,689
Diversification (macro sectors)	-0.87	0.18	-1	-0.26	289,689
Diversification (4-digit sectors)	-0.58	0.27	-1	-0.08	289,689
Diversification (Paris)	-0.85	0.19	-1	-0.5	289,689
Diversification (Regions)	-0.71	0.30	-1	-0.08	289,689

Note: *Firm size* is measured as the total number of (full time equivalent) employees; *Rest of the group size* is measured as the total number of (full time equivalent) employees in firm j's group, except firm j. A group's *Diversification (macro sectors/4-digit sectors/Paris/Regions)* is computed as the opposite of the sum of the squares of all its affiliated firms' employment shares, where each share is the ratio of the total employment of affiliated firms active in a given macrosector (in a given 4-digit industry; in/outside the Paris Area; in a given region) to total group employment. Macrosectors are agriculture, service, finance, manufacturing, energy, automotive. The descriptive statistics displayed in this table are computed using *firm-level* data. Hence, large groups are over-represented and the average group characteristics are larger than those computed using data at the group level and mentioned in footnote 21.

Table A3. ILM activity and group diversification

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(Log) Firm size	0.009***	0.009***	0.009***	0.009***	0.009***	0.009***	0.009***	0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
(Log) Rest of the group size	0.001	0.000	0.001	0.004*	0.001	0.001	0.002	0.004*
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
(Log) Number of affiliated firms	-0.084***	-0.085***	-0.085***	-0.088***	-0.085***	-0.087***	-0.087***	-0.0909***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
State Control	-0.025	-0.020	-0.024	-0.009	-0.024	-0.016	-0.025	-0.013
	(0.024)	(0.022)	(0.023)	(0.017)	(0.023)	(0.021)	(0.022)	(0.018)
Foreign control	-0.043	-0.038	-0.042	-0.029	-0.044	-0.039	-0.043	-0.035
	(0.026)	(0.026)	(0.026)	(0.021)	(0.026)	(0.023)	(0.025)	(0.021)
Diversification (Macrosectors)	-0.006	-0.009						
	(0.007)	(0.007)						
Diversification × Rest of the group size		0.012***						
		(0.003)						
Diversification (4 digit)			0.014*	0.030***				
			(0.006)	(0.006)				
Diversification (4d) × Rest of the group size				0.022***				
				(0.003)				
Diversification (Paris Area)					0.039***	0.022*		
					(0.008)	(0.009)		
Diversification × Rest of the group size						0.024***		
						(0.004)		
Diversification (Region)							0.043***	0.040***
							(0.007)	(0.007)
Diversification (Reg.) × Rest of the group size								0.027***
								(0.004)
N	289,689	289,689	289,689	289,689	289,689	289,689	289,689	289,689
Firm×group effects and year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Dependent variable: Excess probability for firm j to hire a worker originating from the same group as j. *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 affiliated with the same group as firm j. *State Control* is an indicator equal to 1 if the head of the group is state-owned. *Foreign Control* is an indicator equal to 1 if the head of the group is located outside France. A group's *Diversification (macrosectors/4-digit sectors/Paris/Regions)* is computed as the opposite of the sum of the squares of all its affiliated firms' employment shares, where each share is the ratio of the total employment of affiliated firms active in a given macrosector (in a given 4-digit industry; in/outside the Paris Area; in a given French region) to total group employment. Macrosectors are agriculture, service, finance, manufacturing, energy, automotive. The variables *Rest of the group size*, *Number of firms in the group*, *Diversification* are normalized to have zero mean. We control for firm × group fixed effects, and include year dummies to control for macroeconomic shocks common to all firms. 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. Standard errors are clustered at the group level.

A.4 Descriptive Statistics on Positive Shocks

Table A4. Firm closures (2002-2010)

	N. of closing firms	Percentage of closing firms				
	All firms	All firms	< 10 employees	≥ 10 employees	Stand-alone firms	BG firms
2002	134,398	9.03	10.25	4.87	9.35	3.66
2003	130,538	8.68	9.78	4.88	9.00	3.47
2004	135,848	8.92	10.30	3.73	9.30	2.93
2005	123,244	8.13	9.38	3.88	8.52	2.62
2006	128,429	8.21	9.49	3.82	8.60	2.72
2007	136,002	8.54	9.91	3.95	8.95	2.89
2008	115,529	7.15	8.40	2.74	7.51	2.21
2009	158,014	9.63	10.99	5.01	10.13	2.98

Note: We denote as closure a drop in employment from one year to the next by 90% or more. In order to avoid denoting as a closure a situation in which a firm simply changes identifier, we remove all the cases in which more than 70% of the lost employment ends up in a single other firm.

Table A5 reports information about the 84 industries experiencing one or more (simultaneous) large (500 or more employee) firm closures in 2002-2010. The table provides: the NAF industry code; the industry name; the year when one or more simultaneous large closure events occur; the average size (full time equivalent employment) of the closing firm(s) at least 4 years before the closure event.

Table A5. Industries experiencing large firm closures, 2002-2010 (baseline sample)

Sector Code	Sector Name	Closure Year	Average size of closing firm at least 4 years before closure event				
			1	2	3	4	5
101Z	Mining of hard coal	2004	9342,3	2300,1			
143Z	Mining of chemical and fertilizer minerals	2007	1198,3				
151C	Processing/preserving of poultry meat	2004	1357,5				
151F	Cooked meats production/trade	2006	533				
155C	Manufacture of cheese	2009	814,5	1748,5			
155D	Manufacture of other dairy products	2008	625,5				
157C	Manufacture of pet food	2008	2358,5				
158A	Industrial manufacture of bread and fresh pastry	2005	1373				
158H	Manufacture of sugar	2009	1689,5				
158V	Manufacture of prepared meals	2006	1231,5				
159J	Manufacture of cider/other fruit wines	2005	868,7				
159S	Production of mineral water	2005	4339,7				
159T	Production of soft drinks	2005	620				
174C	Manufacture of textile articles, except apparel	2005	609,5				
177C	Manufacture of knitted and crocheted apparel	2005	603,3				
193Z	Manufacture of footwear	2006	513,5				
211C	Manufacture of paper and paperboard	2006	1265,3				
212E	Other printing	2008	1332,7				
221E	Publishing of journals and periodicals	2005	578,5				

222C	Other printing	2008	696				
241E	Manufacture of other inorganic basic chemicals	2007	915,7				
241J	Manufacture of fertilizers and nitrogen compounds	2009	1480,5				
244A	Manufacture of basic pharmaceutical products	2007	3771,3				
251E	Manufacture of other rubber products	2007	1655,3	518,3			
252C	Manufacture of plastic packaging	2007	938,8				
261J	Manufacture/processing of other glass, incl. technical glassware	2004	743,5				
262C	Manufacture of ceramic sanitary fixtures	2007	534				
273G	Cold drawing of wire	2007	590,7				
274C	Aluminium production	2008	594,2				
274D	Aluminium prod./processing	2007	1166,7				
275A	Casting of iron	2004	848				
282D	Manufacture of central heating radiators and boilers	2006	1079,8				
285D	Industrial mechanical engineering	2008	585,5				
287C	Manufacture of light metal packaging	2006	610,8				
287G	Manufacture of bolts and screws	2006	612,3				
291D	Manufacture of fluid power equipment	2004	570,8				
292C	Manufacture of lifting and handling equipment	2004	696				
292D	Repair of machinery	2005	847,5				
295G	Manufacture of machinery for textile/apparel/leather production	2006	830,8				
297C	Manufacture of non-electric domestic appliances	2008	776,5				
311B	Manufacture of electric motors, generators and transformers	2005	593,8				
312A	Manufacture of electronic components	2008	713				
314Z	Manufacture of batteries and accumulators	2006	1244,5				
316A	Manufacture of electric lighting equipment	2009	1279,5				
316D	Manufacture of other technical ceramic products	2005	1102,5				
321C	Manufacture of loaded electronic boards	2009	1700,7				
322B	Manufacture of communication equipment	2008	624				
332B	Manufacture of optical instruments and photographic equipment	2005	534,8				
353C	Manufacture of air and spacecraft and related machinery	2007	2311,8				
361C	Manufacture of office and shop furniture	2006	752,5				
361M	Manufacture of mattresses	2009	640,3				
452B	Construction of other buildings	2008	513,3				

452D	Construction and maintenance of tunnels	2005	1058,5					
503A	Wholesale of motor vehicle parts and accessories	2007	851,3					
511R	Agents specialized in the sale of other particular products	2008	1083					
512A	Wholesale of grain, unmanufactured tobacco, seeds and animal feeds	2009	771					
515C	Wholesale of metals and metal ores	2008	1217					
518G	Wholesale of computers, computer peripheral equipment and software	2009	852					
518L	Wholesale of electric equipment	2007	1353	655	1074	1212	1222	
521A	Retail sale of fruit and vegetables in specialized stores	2007	1893,8					
524H	Retail sale of furniture	2008	563					
526B	Retail sale via home-shopping by specialized catalogue	2008	767					
526G	Door to door sale	2006	1578,7					
526H	Vending machine sale	2006	1065,2					
552E	Holiday and other short-stay accommodation	2009	541,7	1447,7				
553B	Fast food restaurants	2008	3380,2					
555A	Other catering services	2004	2795	1284				
555C	Collective catering under contract	2007	1064	650,2	8096,8			
602B	Regular road transport of passengers	2007	1740,5	593				
602M	Interurban freight transport by road	2009	619,7					
602P	Rent of lorries with driver	2003	1242,2					
631B	Non harbor cargo handling	2009	713,2					
634B	Chartering and transportation organization	2009	534,5					
703C	Management of real estate on a fee or contract basis	2008	646,2					
713C	Renting/leasing of construction, civil engineering machinery and equipment	2009	759,7					
723Z	Computer facilities management activities	2005	565,2	635				
725Z	Repair of computers and peripheral equipment	2005	651					
731Z	R&D in natural sciences and engineering	2008	836					
741C	Accounting, bookkeeping and auditing; tax consultancy	2004	1200,7	771,2				
741G	Management consultancy activities	2009	524,5					
743B	Technical analyses, testing and inspections	2006	1063,5					
748B	Photographic activities	2009	684,5	2004	986,5			
748D	Packaging activities	2008	587,2					
900G	Collection of non-hazardous waste	2009	542,5					

Table A6. Industries Experiencing Large Firm Closures in 2002-2010 (Extended Sample (I))

Sector Code	Sector Name	Closure Year	Avg size of closing firm 4+ yrs before closure event	Closure Year	Avg size of closing firm 4+ yrs before closure event
151E	Industrial production of meat products	2008	557	2009	501,5
245C	Manufacture of perfumes and toiletries	2004	546,5	2005	1977,2
252H	Manufacture of plastic-based technical parts	2008	1199	2009	1438
275E	Casting of light metals	2005	796	2008	552
287Q	Manufacture of metal articles	2004	652	2008	576,5
342A	Manufacture of motor vehicles bodies and trailers	2004	597	2006	1279,7
351B	Building of ships and floating structures	2005	567	2007	4413,7
365Z	Manufacture of games and toys	2008	651,7	2009	533,7
452C	Construction of civil engineering structures	2005	870,7	2009	1701,5
452E	Construction of utility projects for fluids	2004	813,5	2006	515,5
513W	Non-specialized wholesale of food, beverages, tobacco	2005	755,5	2006	4188,2
524L	Retail sale of electrical household appliances	2005	547,5	2010	540,2
524P	DIY retail trade	2004	736,2	2005	1108,7
526A	Retail sale via home-shopping by general catalogue	2004	871,7	2009	567
551A	Hotels and similar accommodation with restaurant	2005	548	2007	1314
553A	Traditional restoration	2008	767	2010	1994,2
602A	Urban passenger land transport	2004	503,5	2009	547
631D	Refrigerating warehousing	2006	2367,2	2008	605,7
702A	Letting of dwellings	2006	628,6	2007	735,7
744B	Advertising agencies	2007	624	2008	502,2

Note: The table reports information on the additional 20 industries where up to 2 large closures occur in two different years. The table provides: the NAF industry code; the industry name; the year of the closure event; the average size (full time equivalent employment) of the closing firm(s) at least 4 years before the closure event.

Table A7. Industries Experiencing Large Firm Closures in 2002-2010 (Extended Sample (II)

Sector Code	Sector Name	Closure Year	Average size of closing firm at least 4 years before closure	Closure Year	Average size of closing firm at least 4 years before closure	Closure Year	Average size of closing firm at least 4 years before closure	Closure Year	Average size of closing firm at least 4 years before closure	Closure Year	Average size of closing firm at least 4 years before closure
151A	Processing and preserving of meat	2004	592,5	2005	752,7	2007	1522,7	2007	827		
361A	Manufacture of seats	2005	1072,2	2008	667,5	2010	1172,2				
453A	Installation works of electrical wiring and fittings	2004	2527,5	2004	8941	2004	732,7	2007	1784,2	2008	946,2
514N	Wholesale of pharmaceutical goods	2008	842,2	2008	1997	2009	578,5				
631E	Non refrigerating warehousing and storage	2005	1885	2005	663,2	2006	2265,5	2008	3143,7		
633Z	Travel agency activities	2008	839,7	2010	1598,5	2010	656,7				
634A	Freight services	2004	1816	2005	3466,2	2005	645,7	2006	548,5	2006	535,2
642C	Wired telecommunications	2007	733	2008	1056,7	2008	506				
721Z	Computer consultancy	2004	1108,5	2005	3078	2005	78	2008	821,5		
742C	Engineering, technical studies	2004	574,7	2006	836,5	2006	1561,3	2006	1036		
748H	Call centers	2004	812,7	2006	1062,5	2009	2487,7	2010	1253,5		
748K	Retail sale of second-hand goods in stores	2006	573,5	2007	529,2	2009	727,5	2009	2182,7		

Note: The table reports information on the additional 32 industries where up to 5 large closures occur in five different years. The table provides: the NAF industry code; the industry name; the year of the closure event; the average size (full time equivalent employment) of the closing firm(s) at least 4 years before the closure event.

Table A8. Pairs of firms with destination firm subject to positive shock in 2002-2010

Year	External Pairs	Same-Group Pairs	Total
2003	330183	6868	337051
2004	351440	7295	358753
2005	373308	7676	380984
2006	386449	8007	394456
2007	392429	8257	400686
2008	383764	8091	391855
2009	365841	7697	373538
2010	334381	6863	341244
Total	2917795	60754	2978549

Note: The Table reports the number of pair-year observations in our sample. In each pair, the destination firm is an affiliated firm active in one of the shocked industries. Same-Group pairs are pairs in which the firm of origin and the firm of destination belong to the same group. The other pairs are denoted as external pairs. We fix the group each firm is affiliated with (if any), which determines whether worker flows within pairs are internal or external, based on their affiliation status one year before the event.

Table A9. Average worker flows in pairs of firms where destination firm is subject to positive shock

				Blue collars		Clerical support		Intermediate		Managers	
Distance from the shock		External Flows	Internal Flows	External Flows	Internal Flows	External Flows	Internal Flows	External Flows	Internal Flows	External Flows	Internal Flows
≤ -4	Mean	0.01896	0.07326	0.00785	0.01934	0.00490	0.01445	0.00354	0.017656	0.00272	0.02074
	Sd	0.09474	0.20185	0.06175	0.10503	0.04407	0.08512	0.04362	0.09174	0.03744	0.10858
	N	532768	11598	530589	11385	530589	11385	530589	11385	530589	11385
$[-3, 0)$	Mean	0.02001	0.07404	0.00801	0.01998	0.00505	0.01429	0.00397	0.01822	0.00304	0.02086
	Sd	0.09587	0.20242	0.06167	0.10666	0.04531	0.08269	0.04517	0.09727	0.03778	0.10366
	N	1048675	22402	1044834	21961	1044834	21961	1044834	21961	1044834	21961
$[0, 3]$	Mean	0.01943	0.07086	0.00740	0.01877	0.00554	0.01605	0.00368	0.01586	0.00287	0.01969
	Sd	0.09486	0.19433	0.06052	0.10212	0.04772	0.08850	0.04232	0.08794	0.03577	0.09798
	N	1175735	24123	1170861	23667	1170861	23667	1170861	23667	1170861	23667
≥ 4	Mean	0.01767	0.06755	0.00498	0.01183	0.00557	0.01663	0.00353	0.01588	0.00363	0.02330
	Sd	0.09090	0.18483	0.0479	0.07042	0.05279	0.09320	0.03997	0.08797	0.03890	0.09803
	N	160617	2631	160353	2585	160353	2585	160353	2585	160353	2,585

Note: The table reports the average bilateral worker flow within pairs of firms where the destination is a group affiliated firm experiencing a positive shock (a large competitor closure) in 2002-2010. The bilateral worker flow is defined as the ratio of workers hired by BG-affiliated firm j from firm k in year t, divided by the total number of workers hired by firm j in year t. External flows are bilateral flows between firms that are external market partners. Internal flows are bilateral flows between firms that are same-group (ILM) partners. We fix the group each firm is affiliated with (if any), which determines whether worker flows within pairs are internal or external, based on their affiliation status one year before the event. The table also provides disaggregate flows for each professional category. The first row reports average flows in the years before our event window, i.e. 4 or more years before the positive shock. The second row reports average flows pre-treatment, within the event window. The third row reports average flows post treatment, within the event window. The last row reports average flows 4 or more years after the large closure event.

Table A10. Average pre-event performance of positively shocked firms

ILM Access	Market Shares	N	ROA	N
Below Median	0.00436	9041	0.06107	8030
Above Median	0.00860	9171	0.06363	8340
Top Quartile	0.01383	4435	0.05490	3982
Top Decile	0.02209	1741	0.05453	1589
95th Percentile	0.02966	852	0.04668	784

Note: The table reports the average pre-event performance of BG firms that experience a positive shock (a large competitor closure) in 2002-2010. The performance measures reported are market share (in sales) and Return on Assets (EBITDA over Total Assets). Both measures are averaged over the pretreatment period within the event window (i.e. over event years $\tau \in [-3, 0)$). The different rows report average pre-event performance for shocked BG firms with different levels of *ILM Access*. *ILM Access* for shocked BG firms ranges between 0 and 277017 workers: the median is equal to 1 worker, the 75th percentile is equal to 35 workers; the 90th percentile is equal to 207 workers, the 95th percentile to 919 workers.

A.5 Positive shocks: Further Robustness Checks and Additional Results

A.5.1 Including industries with multiple shocks in different years

The event study we perform in Section 4 can be extended to also include the (few) industries that are affected by multiple large closure events occurring in different years during our observation period. Sandler and Sandler (2014) show, with Monte Carlo simulations, that when multiple events occur focusing on the first one and disregarding the subsequent ones yields biased estimates, as it mechanically produces spurious pre- and post-event trends, if in the true model multiple events are additive (i.e. it is plausible that subsequent events also have an effect on the outcome). Similarly, duplicating observations, generating one line per individual-event and time, also introduces a bias. Instead, allowing for more than one event-time dummy to be turned on in any given year produces unbiased estimates.

Therefore, as in the baseline model, we set the size of the event window to contain both the event year as well as three periods before and after the event, and allow more than one event-time dummy to be equal to one in any year. More specifically, we add a set of non mutually exclusive dummies reflecting the distance from the different events: if a given pair of firms, in a given year, is both two periods before an event and one year after another event, both relevant dummies are equal to 1.

Results are displayed in Table A11. Columns (1)-(2) show results obtained when we perform our analysis on an extended sample that includes both the 84 industries that experience one large closure event or several simultaneous events (as in our baseline analysis), and an additional 20 industries that experience up to 2 non simultaneous events over the sample period. Columns (3)-(4) show results obtained when, alongside the 84 baseline industries, we also include industries that experience up to 5 non simultaneous events (which increases the number of industries in the analysis to 116). The results are qualitatively similar to the baseline, however the presence of non simultaneous events with overlapping event windows makes the estimates less precise.

A.5.2 Event window size

We also explore robustness to an alternative event window, with pre-treatment starting at $\tau = -4$ and post-treatment ending at $\tau = +2$.

Table A11. Impact of large competitor closures on worker flows from ELM and ILM firms - Further robustness checks

	Extended Sample (I)		Extended Sample (II)		Asymmetric Event Window		
	(1)	(2)	(3)	(4)		(5)	(6)
Distance from shock	External flows	Internal flows	External flows	Internal flows	Distance from shock	External flows	Internal flows
-3	0.00031*	0.00378	0.00021	0.00197	-4	0.00021	0.00822
	(0.00015)	(0.00239)	(0.00011)	(0.00210)		(0.00036)	(0.00462)
-2	0.00026*	0.00249	0.00014	0.00276	-3	0.00024	0.00305
	(0.00011)	(0.00175)	(0.00010)	(0.00149)		(0.00019)	(0.00272)
-1	-	-	-	-	-2	0.00021	0.00250
	(-)	(-)	(-)	(-)		(0.00011)	(0.00205)
0	0.00036***	0.00265	0.00030***	0.00163	-1	-	-
	(0.00011)	(0.00195)	(0.00009)	(0.00165)		(-)	(-)
1	0.00029	0.00788***	0.00030**	0.00561***	0	0.00024*	0.00543*
	(0.00015)	(0.00196)	(0.00011)	(0.00149)		(0.00010)	(0.00231)
2	-0.00011	0.00795*	0.00012	0.00564*	1	0.00013	0.01252***
	(0.00021)	(0.00322)	(0.00019)	(0.00219)		(0.00019)	(0.00287)
3	-0.00018	0.00795	0.00008	0.00347	2	-0.00030	0.01664**
	(0.00031)	(0.00669)	(0.00026)	(0.00250)		(0.00027)	(0.00506)
Pair FE	Yes		Yes		Yes		
N	4672679		5813309		2975794		

Note: The table reports the coefficients $\widehat{\alpha}^{Int}_{\tau} - \widehat{\alpha}^{Int}_{-1}$ and $\widehat{\alpha}^{Ext}_{\tau} - \widehat{\alpha}^{Ext}_{-1}$ estimated from equation (3). Date $\tau = 0$ is the year of the positive shock, i.e. the first year in which the large competitor is no longer active in a given industry. The flows are measured as the ratio of workers hired by a BG-affiliated firm j (active in a shocked industry) from firm k in year t, to the total number of workers hired by firm j in year t. We include firm-pair fixed effects and year dummies in our specification. Columns (1)-(4) report results when we include in the sample industries that experience multiple closures in different years. Columns (1)-(2) show results when we exploit large closure events occurring in the (baseline) 84 industries that experience one large closure event or several simultaneous events, *and* an additional 20 industries that experience up to 2 non simultaneous events over the sample period. Columns (3)-(4) show results when we exploit large closure events occurring in the baseline 84 industries, *and* an additional 32 industries that experience up to 5 non simultaneous events over the sample period. Columns (5)-(6) instead explore robustness to an alternative event window, with pre-treatment starting at $\tau = -4$ and post-treatment ending at $\tau = +2$. Standard errors in parenthesis are clustered at the industry and group level. Significance levels are * 5%, ** 1%, *** 0.1%.

A.6 Negative Shocks: Descriptive Statistics

Table A12. Pairs of firms with firm of origin that eventually closes in 2002-2010

Year	External Pairs	Same-Group Pairs	Total
2002	283613	9953	293566
2003	297178	10305	307483
2004	309502	10650	320152
2005	289145	9530	298675
2006	253422	7863	261285
2007	193316	5954	199270
2008	132269	3667	135936
2009	76377	1927	78304
Total	1834822	59849	1894671

Note: The Table reports the number of pair-year observations in our sample. In each pair, the firm of origin is an affiliated firm that eventually closes in our sample period. Same-Group pairs are pairs in which the firm of origin and the firm of destination belong to the same group. The other pairs are denoted as external pairs. We fix the group each firm is affiliated with (if any), which determines whether worker flows within pairs are internal or external, based on their affiliation status at $\tau = -2$.

Table A13. Average worker flows in pairs of firms where the firm of origin will eventually close

				Blue collars		Clerical support		Intermediate		Managers	
Distance from closure		External Flows	Internal Flows	External Flows	Internal Flows	External Flows	Internal Flows	External Flows	Internal Flows	External Flows	Internal Flows
< -4	Mean	0.02762	0.09846	0.01087	0.02196	0.00683	0.01823	0.00584	0.02500	0.00408	0.03327
	Sd	0.12076	0.24283	0.07714	0.11810	0.05882	0.10475	0.05695	0.11951	0.04733	0.14167
	N	363393	10247	363386	10247	363386	10247	363386	10247	363386	10247
-4	Mean	0.02767	0.10477	0.01027	0.02379	0.00702	0.02147	0.00617	0.02807	0.00420	0.03143
	Sd	0.11968	0.24760	0.07478	0.12124	0.05818	0.11381	0.045827	0.12323	0.04715	0.13570
	N	241034	7366	241027	7366	241027	7366	241027	7366	241027	7366
-3	Mean	0.03018	0.11030	0.01102	0.02348	0.00776	0.02153	0.00667	0.02932	0.00473	0.03596
	Sd	0.12478	0.25357	0.07650	0.11839	0.06213	0.11166	0.06070	0.13060	0.05021	0.14709
	N	291097	9641	291090	9641	291090	9641	291090	9641	291090	9641
-2	Mean	0.03430	0.12110	0.01218	0.02623	0.00854	0.02315	0.00773	0.03021	0.00585	0.04151
	Sd	0.13271	0.26220	0.07997	0.12769	0.06524	0.11476	0.06504	0.13075	0.05588	0.15890
	N	329081	11851	329074	11851	329074	11851	329074	11851	329074	11851
-1	Mean	0.02916	0.22996	0.01013	0.06966	0.00762	0.04624	0.00608	0.05714	0.00534	0.05692
	Sd	0.12095	0.35470	0.07040	0.19256	0.05818	0.14454	0.05311	0.15591	0.05149	0.16484
	N	318243	11488	318236	11488	318236	11488	318236	11488	318236	11488
0	Mean	0.02798	0.32135	0.00933	0.10190	0.00708	0.06970	0.00586	0.06982	0.00570	0.07993
	Sd	0.12405	0.40686	0.06785	0.23397	0.05887	0.18196	0.05268	0.16634	0.05456	0.19846
	N	291974	9256	291967	9256	291967	9256	291967	9256	291967	9256

Note: The table reports the average bilateral worker flows within pairs of firms where the firm of origin is a group affiliated firm that will eventually close in 2002-2010. Bilateral flows are measured as the ratio of workers moving from closing BG-affiliated firm j to firm k in year t, to the total number of workers displaced by firm j in year t. External flows are bilateral flows between firms that are external market partners. Internal flows are bilateral flows between firms that are same-group (ILM) partners. Event date 0 is the last year of activity of the closing firm. We fix the group each firm is affiliated with (if any), which determines whether worker flows within pairs are internal or external, based on their affiliation status at $\tau = -2$, i.e. two years before the closure year. The table also provides disaggregate flows for each professional category. The first row reports average flows in the years before our event window, i.e. more than 4 years before the closure year.

Table A14. Average worker internal flows below and above the 50 threshold

Distance from closure		Below 50	Above 50
< -4	Mean	0.08538	0.05948
	Sd	0.20945	0.18476
	N	271	224
-4	Mean	0.07852	0.10035
	Sd	0.18340	0.23667
	N	223	139
-3	Mean	0.10069	0.08257
	Sd	0.21946	0.18862
	N	341	187
-2	Mean	0.10167	0.07541
	Sd	0.21329	0.19127
	N	445	207
-1	Mean	0.14434	0.18588
	Sd	0.26773	0.30085
	N	433	209
0	Mean	0.29341	0.29407
	Sd	0.38431	0.38010
	N	370	177

Note: The table reports average worker flows within pairs of firms where the firm of origin is a group affiliated firm that will eventually close in 2002-2010. the table focuses on internal flows, i.e. flows within pairs of firms that are affiliated with the same group. Moreover the table focuses on firms of origin that employ between 40 and 60 employees in the last year of their activity (i.e. at $\tau = 0$), and displays bilateral worker flows for those firms of origin that are below/above the 50 thresholds. Bilateral flows are measured as the ratio of workers moving from closing BG-affiliated firm j to firm k in year t, to the total number of workers displaced by firm j in year t. We fix the group each firm is affiliated with (if any), which determines whether worker flows within pairs are internal, based on their affiliation status at $\tau = -2$, i.e. two years before the closure year. The first row reports average flows in the years before our event window, i.e. more than 4 years before the closure year.

Table A15. Test of balanced covariates around the 50-employee threshold

	ROA	Value Added per Worker	Capex	Leverage	Cash
			Size at closure: 40-49		
Mean	0.025	56.301	247.744	0.240	715.148
Standard deviation	(0.387)	(73.895)	(1016.052)	(0.594)	(3101.114)
N	1018	1092	1043	1018	1043
			Size at closure: 50-60		
Mean	0.070	55.035	321.946	0.202	812.319
Standard deviation	(0.472)	(66.546)	(1278.947)	(0.460)	(4125.846)
N	585	642	601	585	601
Unconditional difference	-0.045*	1.267	-74.202	0.039	-97.160
	(0.023)	(3.449)	(60.922)	(0.027)	(193.763)
Conditional difference	0.0200	3.035	-17.391	-0.046	-195.544
	(0.017)	(5.268)	(53.354)	(0.026)	(146.889)

Note: The table reports descriptive statistics for BG-affiliated firms redeploying workers to firms of the same group, separately for firms in the 40-49 and 50-60 size windows at closure. The bottom panel (Conditional difference) reports the coefficient of a dummy identifying firms above 50 employees from a regression including year indicators and industry fixed effects, with standard errors clustered at the group level. Significance levels are * 5%, ** 1%, *** 0.1%.

Table A16. Average worker flows to unemployment

Distance from closure		Flows from SA firms	Flows from BG firms
< -4	Mean	0.16894	0.13991
	Sd	0.35173	0.36817
	N	138604	16663
-4	Mean	0.15732	0.11366
	Sd	0.32273	0.24862
	N	109971	11404
-3	Mean	0.15456	0.10663
	Sd	0.31178	0.23700
	N	155910	14601
-2	Mean	0.16308	0.10292
	Sd	0.30860	0.17746
	N	207588	17978
-1	Mean	0.23758	0.13987
	Sd	0.38239	0.26167
	N	200125	17768
0	Mean	0.20569	0.14094
	Sd	0.39834	0.28764
	N	227572	18489

Note: The table reports average flows to unemployment from stand-alone firms and BG-affiliated firms. We fix the group each firm is affiliated with (if any), which determines whether the firm of origin is a stand-alone firm or a BG-affiliated firm, based on their affiliation status at $\tau = -2$, i.e. two years before the closure year. Flows to unemployment are measured as number of workers moving to unemployment normalized by the size of the firm's workforce. The first row reports average flows in the years before our event window, i.e. more than 4 years before the closure year.

Table A17. Probability of closure, BG firms versus stand-alone firms

Variables	(1)	(2)
BG Affiliated	-0.013***	-0.002***
	(0.001)	(0.000)
(Log) Firm Size	-0.030***	-0.013***
	(0.000)	(0.000)
N	10,858,055	9,982,866
Industry FE	Yes	Yes

Note: The table reports results from a linear probability model estimating the probability of closure of French firms in 2002-2010. *BG Affiliated* is a dummy taking value one if the firm is group-affiliated, and zero if the firm is a stand-alone. In column (1) we allow the BG status to vary with time. In column (2) BG status is fixed 2 years before the closure (for those firms that eventually close), i.e. when soon-to-close firms start to display a decline in performance. This is to avoid regarding as stand-alone closures cases of BG units that are spun-off by the group in the run-up to a closure. In both columns we control for the log of firm size (i.e., of full-time equivalent employment) and industry fixed effects. Standard errors in parenthesis are clustered at the firm (group) level for stand-alone (group affiliated) firms. Significance levels are * 5%, ** 1%, *** 0.1%.

A.7 Labor market regulation in France

In this section we briefly summarize the main pillars of employment protection regulation in France, regarding the termination of indefinite duration contracts. We refer to Abowd and Kramarz (2003) for more details on both indefinite and fixed duration contracts.

The termination of indefinite duration contracts under French Labor Law falls under different categories: dismissal for economic reasons (be it a single or a collective dismissal); dismissal for personal cause (be it for "serious reason" or "very serious misconduct"); early and normal retirement. With the exception of terminations for "very serious misconduct", in all other terminations the employer must (i) observe a mandatory advance notice period and (ii) pay a severance payment. The advance notice period (the delay between the formal notice letter announcing the termination and the end of the employment contract) varies between 1 and 3 months, depending on the worker's seniority. Severance payments must be paid to workers with at least two years seniority: for every year of seniority, the employer pays 1/10 of the wage if the worker is paid by the month. An additional payment is due for every year of service beyond 10. Employees who are fired for economic reasons also enjoy employment priority within the firm for 1 year after the termination date, and have 1 year to dispute the dismissal.

Dismissals can only be justified in case of a "genuine and serious cause". Valid economic reasons for termination include the destruction of the worker's job, the transformation of the job or the worker's refusal to sign a new contract when a modification of the labor contract is necessary. These events are usually due either to technological change within the firm or bad economic conditions. The employer must follow a strict procedure in notifying the dismissal and providing a justification for it. If the procedure is overlooked, or the dismissal deemed unfair by a court, the employee is entitled to additional compensation (normally at least 6 months salary). While a firm's closure represents a legitimate cause for dismissal, common procedural errors can still trigger additional compensation to employees in case of dismissals prompted by the firm's closure.

In sum, the complex termination procedure and the penalties involved in case of a successful dispute impose non negligible termination costs that add to the advance notice and severance payment. This is particularly true in the case of *large* collective terminations in firms with 50 or more employees. Indeed, the termination of less than 10 workers during a 30-day period must follow a procedure similar to individual terminations: the employer must consult the personnel delegate or the union representatives, notify the Ministry of Labor in writing, provide an exit interview to the employee and possibly a retraining program. However, for firms with 50 or more employees, the dismissal of at least 10 workers during a 30-day period requires a much more complex procedure, detailed by the 2 August 1989 law. Before engaging in the collective termination, these larger firms must formulate a "social plan" (recently renamed as "employment preservation plan") in close negotiation with staff and union representatives. This is mandatory also in case of collective terminations prompted by the firm's closure.

The employment preservation plan must try to limit the total number of terminations, and facilitate reemployment of the terminated workers (e.g., by retraining and redeploying them internally or within the firm's group if possible). The procedure required to formulate and negotiate the plan is fairly long, especially if it is disputed. It involves several meetings with staff and union representatives. During this period, the Ministry of Labor is kept informed about the process, and must verify that the procedure has been followed correctly. Along the process, the plan can be disputed by unions and staff representatives, for instance on the ground that not all dismissals are justified or not all reallocation options have been considered.