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Abstract

We explore how business groups use internal labor markets (ILMs) in response to changing economic conditions. We show that following the exit of a large industry competitor, group affiliated firms expand and gain market share by increasing their reliance on the ILM to ensure swift hiring, especially of technical managers and skilled blue collar workers. The ability to take advantage of this shock to growth opportunities is greater in firms with closer access to their affiliates' human capital, as geographical proximity facilitates employee relocations across units. Overall, our findings point to the ILM as a prominent mechanism making affiliation with a business group valuable at times of change. For the ILM to perform its role in the face of industry shocks, group sectoral diversification must be combined with geographical proximity between affiliates.

JEL Classification: G30, J20, L22

Keywords: Labor market frictions

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Exploiting Growth Opportunities: The Role of Internal Labor Markets*

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January 4, 2023

Abstract

We explore how business groups use internal labor markets (ILMs) in response to changing economic conditions. We show that following the exit of a large industry competitor, group-affiliated firms expand and gain market share by increasing their reliance on the ILM to ensure swift hiring, especially of technical managers and skilled blue collar workers. The ability to take advantage of this shock to growth opportunities is greater in firms with closer access to their affiliates' human capital, as geographical proximity facilitates employee relocations across units. Overall, our findings point to the ILM as a prominent mechanism making affiliation with a business group valuable at times of change. For the ILM to perform its role in the face of industry shocks, group sectoral diversification must be combined with geographical proximity between affiliates.

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 their business when conditions change. The nature of organizations that are better able to adapt to such changing economic conditions is a directly associated question. This paper addresses these issues by investigating the role of Internal Labor Markets (ILMs, hereafter) in allowing widespread organizations, business groups (BGs), to accommodate positive shocks likely to entail labor adjustments in their units. While hiring costs and asymmetric information affect the hiring process on the external labor market, such frictions should be less severe within an organization, i.e. when workers are reallocated across its units. By adapting rapidly thanks to their ILM, these organizations should be in a better position to seize growth opportunities. To assess the validity of this reasoning, we construct key variables and design our empirical analysis guided by a model exploring how multi-firm entities (such as business groups) use ILMs in response to positive shocks to their growth opportunities. By exploiting the institutional hurdles to internal mobility, we measure firms' access to their group's ILM and investigate whether better access facilitates firms' expansion and performance. This allows us to identify which group and firm characteristics increase the value of the ILM.

The data requirements to tackle our research questions are multiple. First, we need to identify positive idiosyncratic shocks that hit part of an organization. Second, we must measure the subsequent employment flows towards the shocked units, distinguishing those that occur with the organization from those that do not. For this purpose, we need to observe the structure of the business organization, i.e. its constituting units. Finally, we must observe the economic outcomes of the shocked entities, including employment and market shares, as well as the characteristics of the entities from which worker flows originate. Unique data sources provided by the French statistical institute (INSEE) are perfectly suited to our purposes: they 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.

To guide our empirical analysis, we build a simple model to study the internal vs external labor adjustment in a multi-firm organization when one of its units is hit by a positive shock. The model allows us to unveil the *ILM Effect*: when hiring internally is less frictional than hiring on the external market, the shocked unit relies as much as possible on the group's ILM to expand its workforce. We also show that an efficient ILM reallocates workers from low to high MRPL (marginal revenue productivity of labor) units in response to the shock. This worker redeployment contributes to a reduction in within-group labor misallocation. The ability to use an ILM in response to a positive shock creates value in two ways. First, hiring on the external market is replaced by internal hiring, thereby saving on adjustment costs. Second, the (positively) shocked unit is able to expand more in response to the growth opportunity.

Then, we test our model predictions. We study whether groups rely on their ILM when a member firm experiences an unexpected growth opportunity, as captured by the death of a large competitor. To do so, we use a difference-in-differences approach that exploits variation in the timing of 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. This allows us to investigate how a group manages its human capital in response to a favorable demand shock, and to which extent the growth of the shocked group's affiliate is facilitated by the group's ILM.

For each group-affiliated firm active in the positively shocked industries, we identify the set of labor market partners from which it actually or potentially hires workers. We then apportion the observed flows of workers into those coming from ILM partners (firms that belong to the same group) and those coming from external labor market partners. Finally, we compute the *share of internal hires* as the fraction of total hiring that originates from ILM partners and we study how this share evolves around the closure event. Our results show that BG firms use their ILM to adjust to the shock: after a large competitor closure, their *share of internal hires* increases by 17% to 26% with respect to the pre-event baseline. Interestingly, ILM use is mainly driven by the hiring of STEM-skilled managers (engineers, scientists, and other professionals with technical skills) and skilled blue collar workers, for whom search and training costs are large on external markets.[1] Furthermore, positively shocked BG firms draw human capital predominantly from group affiliates that display low productivity and poor expansion opportunities in the years preceding the shock.

We then test the model prediction that easier access to the ILM helps group-affiliated firms take better advantage of growth opportunities. We measure *ILM Access* of a shocked affiliated firm as the workforce employed in affiliates of the same group (i) located within the same local labor market as the (shocked) firm, but (ii) active in different (hence non-shocked) industries. By avoiding regulatory barriers to worker transfers and by facilitating information exchange about workers' quality, geographical proximity facilitates internal labor reallocation. BG firms with better *ILM Access* are shown to expand more and gain more market share in the aftermath of a competitor's death.[2] Whereas within-group industry-diversification (which creates scope for both internal labor

[1] See Abowd and Kramarz (2003), Kramarz and Michaud (2010), Blatter, Muehlemann, and Schenker (2012).

[2] This echoes multiple old and recent claims that firms' growth may be constrained by human capital frictions (see Penrose (1959) and Parham (2017)). The idea that a lack of skilled human capital may hamper growth is also supported

market *and* capital market activity) helps BG firms' expansion, it is geographical proximity within the group's workforce that plays a key role. These results show that ILMs are an important driver of an organization's growth, overlooked in the literature which focused on internal *capital* markets as a gateway to investment opportunities (see e.g. Giroud and Mueller (2015)).

Finally, we rely on our model to quantify the extent of within-group labor misallocation due to a shocked unit's constrained access to the ILM. This exercise confirms a key take-away of our empirical analysis: in our setting, where the shock has an industry dimension, diversification across industries (that exposes group units to idiosyncratic shocks) must be paired with geographical proximity between group units to promote value creation through the ILM. Indeed, groups that are highly diversified but where the vast majority of employees are distant from the shocked unit exhibit the most important within-group misallocation after the shock: we calculate that consolidated profits for such groups would increase by 0.2 to 0.3 percent if their ILM redeployed just *one* additional average worker (i.e. not a top executive) to the shocked unit. This is an important effect, in the ballpark of 1/5 to 1/9 of the estimated contribution of CEO's continued employment to firm profits (see Bennedsen, Perez Gonzalez, and Wolfenzon (2020)).

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.[3] Our results suggest that these motives explain only in part why organizations 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), Belenzon and Tsolmon (2015)). 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.[4] Giroud and Mueller (2015) provide evidence that, by alleviating financial constraints, internal capital markets also allow conglomerates

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).

[3]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 (2013), Ke, Li, and Powell (2018) and Kostol, Nimczik, and Weber (2019).

[4]See 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)).

to take better advantage of positive shocks to investment opportunities.[5] Our paper adds to their work, showing that in the presence of hiring frictions internal *labor* markets also help organizations to take advantage of growth opportunities.[6]

In contrast with the internal capital market literature, research on internal *labor* markets is limited.[7] Focusing on adverse shocks, Tate and Yang (2015) provide evidence that multi-divisional firms use ILMs when coping with plant closures, and Cestone, Fumagalli, Kramarz, and Pica (2021) show that employment protection regulation is a major driver of ILM activity in response to adverse shocks. We add to these contributions, showing 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 to adjust in good times.

By setting up a simple model of the ILM and deriving testable empirical predictions, our paper can provide a blueprint for research on internal labor markets. In a paper subsequent to ours, Huneeus, Huneeus, Larrain, Larrain, and Prem (2021) confirm one of our predictions, i.e. that ILM activity intensifies in business groups following shocks. Differently from them, we can rely on balance sheet data to test other predictions from our model. We show for instance that workers are reallocated from low to high productivity units within the ILM, in line with the result that intra-group labor reallocation aims at reducing the wedge between marginal revenue productivity of labor across units. We are also in a position to show that BG firms with better access to the ILM grow more and build more market share. Finally, relying on our model and using data on Value Added per Worker, we build a measure of intra-group labor misallocation that helps us understand what group characteristics hinder or promote value creation through the ILM.

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 (Luciano and Nicodano (2014), Belenzon, Lee, and Patacconi (2021)). Indeed, we 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

[5]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.

[6]Our paper is also related to Giroud and Mueller (2019), who study the transmission of cash flow shocks across units of multi-establishment groups. In both their model and ours, non-shocked units partly absorb a shock hitting another unit in their network. The key driver behind the results is difficult access to a scarce resource: external financing in their case, human capital in our case.

[7]Faccio and O'Brien (2021) 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.

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, which would make the parent liable vis-a-vis its subsidiaries' debt holders).

Finally, the paper is related to a growing literature that explores how firms organize production in hierarchies to optimize their use of knowledge workers (Garicano (2000)). Caliendo and Rossi-Hansberg (2012) predict that firms which grow substantially do so by adding more layers of management to the organization. Our findings suggest that when faced with expansion opportunities, group-affiliated firms draw on the group's ILM to reduce the costs and delays associated with hiring employees in the top layers of the organization (STEM-skilled managers) and other high-knowledge occupations.

The paper proceeds as follows. In Section 2 we describe the data; we then present descriptive evidence on French business groups and on group firms' propensity to hire on the ILM. In Section 3 we present the model and lay out testable predictions. The empirical strategy is described in Section 4, and empirical results are discussed in Section 5. Section 6 concludes.

2 Data, Descriptive Evidence, Measures of Workers Mobility

2.1 Data sources

We want to explore empirically whether the ability to draw on human capital via the ILM enables group-affiliated firms to better respond to positive shocks to growth opportunities. This 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. Fourth, we want to identify the death of large competitors which we use as shocks to growth opportunities. All such information is available for France, by putting together three data sources gathered by the French statistical institute, INSEE (*Institut National de la Statistique et des Études Économiques*).

The identification of business group structures is based on the yearly survey run by INSEE called LIFI (*Enquête sur les Liaisons Financières entre sociétés*). 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 even among listed firms ownership concentration is very high (see Bloch and Kremp (1999)). To sum up, for each firm in the French economy, LIFI enables us to assess whether the firm is group-affiliated or not and, for BG-affiliated firms, to identify the head of the group and all the other firms affiliated with the same group.

Our data source on firm-to-firm worker mobility 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 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. The data set also provides the fiscal identifier of the firm owning 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 (as obtained from the INSEE NAF rev. 1, 2003). 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, each wave includes not only information on the individual-plant relationships observed in year t, but also in year $t-1$: this allows us to identify workers transiting from one firm to another across two consecutive years. The DADS data also allows us to precisely identify firm closures, as we explain in Section 4.4.

The third data source 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 provides accounting information, including firm's assets, EBITDA, Value Added, sales, capital expenditures, 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.1) 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 remove from the data set those employers classified as "*employeur particulier*" (individuals employing workers providing services in support of the family, e.g. cleaners, nannies, caregivers) and employers classified as "fictitious" because the code identifying the firm or plant communicated by the employer to the French authority is incorrect.

2.2 Business groups in France

Business groups are networks of independent legal entities ("affiliates") controlled by a common owner. Groups account for a large fraction of the economic activity in both developed and developing economies.[8] Based on our comprehensive data on the population of listed *and* private group-affiliated companies, we can provide a thorough picture of the prevalence and characteristics of groups in the French economy.

The number of business groups with a French-based headquarter has increased from 31,990 in 2002 to 48,274 in 2010. Nevertheless, this increase hides a relative stability: firms affiliated to groups represent a constant 5% of the total population of firms over our sample period, accounting for 40% of total employment and (more than) 60% of value added, as shown in Figure 2, panel (a). Groups are important players in all the sectors of the economy, with the exception of Agriculture, where affiliated firms account for 2.5% of total employment. In the rest of the economy the presence of groups is strong, as high as 57.8% in Manufacturing, 55.8% in Finance and 33.3% in Services other than Finance. Groups can be pervasive in some industries, such as Energy and Automotive, where almost all employment is accounted for by BG firms.

The average group in the French economy is mid-sized: it employs 250 (full-time equivalent) workers and comprises 4.7 affiliates, each of them employing 48 workers. On average, groups display a limited degree of diversification, spanning over 2.7 different (four-digit) industries and 1.6 different regions: group concentration of employment across four-digit industries amounts to 0.82, and concentration of employment across regions to 0.93 (we measure group concentration across industries/regions using an HHI based on the share of total group employment in the different industries/regions). Business groups exhibit entry and exit of affiliates: in a given year both the average

[8]Using ownership data on listed companies in 43 countries, Faccio, Mork, and Yavuz (2021) 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). However, alongside large renowned groups, which are often multinational enterprises, mid-sized business groups form the productive fabric of many economies.

percentage of affiliates that is new to a group and the average percentage of affiliates leaving a group range between 15 and 20%.

The availability of data on the entire population of groups, not only large ones, allows us to uncover interesting cross-group heterogeneity hidden by such average figures. Indeed, the group-size distribution is very skewed. Ranking French groups in ten deciles based on their full-time equivalent total employment reveals that groups in the top decile are very different from the others along many dimensions: as shown in Figure 2, panel (b), groups belonging to the top decile employ 2,114 workers on average, and are 50 times bigger than groups belonging to the rest of the population, which employ only 43 workers on average. Additionally, Figure 3 shows that top-decile groups (in terms of size) have on average 20 affiliates (panel (a)), each employing 245 workers (panel (b)); they operate in 6.3 different four-digit industries (panel (c)) and in 3.4 different regions (panel (d)); industry concentration is approximately 0.65 (panel (e)) and region concentration 0.7 (panel (f)). Instead, groups in the rest of the population have, on average, 3 affiliates, employ 25 workers per-unit; they operate in 2.3 different four-digit sectors and 1.4 regions; their industry concentration is 0.84 and region concentration 0.95.

The overall picture that emerges is that (relatively) few diversified groups coexist with many smaller, more focused groups.

2.3 Measuring business groups' propensity to hire internally

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 BG 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 a BG 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 intensive in occupations among which mobility is naturally high or geographically close to each other. In other words, group structure is endogenous (for instance in terms of both occupations and locations) and potentially affects within-group mobility patterns. Therefore, to provide meaningful, yet descriptive, evidence that the ILM facilitates within-group mobility, we analyze workers' mobility patterns controlling for firm-specific (possibly time-varying) "natural" propensity to absorb workers transiting between given occupations and locations. We do so first by looking at all job movers, and then, progressively, by conditioning on the characteristics of the occupations and the locations of origin and destination. We do not claim that this approach cleanly identifies the ILM effect, and consider it as still descriptive, because other (unobservable) factors beyond occupations and locations plausibly affect within-group mobility patterns. Section 4.1 discusses how it is instead possible to overcome the challenges in the identification of the ILM effect when investigating groups' response to a positive shock.

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. By definition, there is no variation in $BG_{i,k,j,t}$ for stand-alone firms, hence $\gamma_{c,j,t}$ is identified only for BG-affiliated firms of destination. 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.2 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. The first row of Table 1 reports descriptive statistics of these excess probabilities, showing an average of about 5 percentage points.[9] The Table also reports the distribution of the estimated excess probabilities, documenting a pronounced heterogeneity across firms: the estimated $\widehat{\gamma}_{j,t}$ is positive only for firms belonging to the top quartile or decile of the distribution. The same pattern emerges from the excess probabilities estimated by conditioning on the occupations and the locations of origin and destination, that we present next. Clearly, not all group-affiliated firms disproportionally hire from the internal market. We will explore later how much of this heterogeneity relates to the pronounced differences across French groups documented in Section 2.2, and in particular to group diversification.

In the second row of Table 1, 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.[10] In this case for each BG firm j at time t we obtain as many estimated $\widehat{\gamma}_{c,j,t}$ as local labor market pairs, that we then aggregate at the firm-level taking simple averages to obtain the firm-level excess probabilities $\widehat{\gamma}_{j,t}$. 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 (6.3 percentage points, see row 3 of Table 1), suggesting that *geographical proximity favors ILM hiring* more than external hiring.

Next we condition on occupations and 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. Aggregating at the firm level, we find that the excess probability is about 9.5 percentage points (see row 4 of Table 1), thus higher than the "unconditional" probability estimated without controlling for occupation-pair effects. This is in line with the fact that the propensity to hire internally is more limited for those occupations that experience the largest flows in the economy, namely non-managerial occupations (as shown in Tables A5 and A6 in Appendix A.2.4).[11] Average excess probabilities remain high (just above 7 percentage points, row 5 of Table

[9] Tables A2 and A3 in Appendix A.2.2 report the estimated excess probabilities for each year in our sample period, showing values that are pretty stable over time.

[10] 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.

[11] 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. The excess probabilities estimated at the occupation pair-firm level $\widehat{\gamma}_{c,j,t}$ turn out to be lower for occupations that experience relatively larger flows in the economy (e.g., non-managerial occupations,), hence the "unconditional" excess

1) 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.*

Finally, substantial preference for internal hiring appears even when accounting for firms' natural propensity to hire workers transiting between specific occupation$\times$locations pairs. Indeed, excess probabilities are about 10 percentage points when we control for firm of destination$\times$local labor market pair $\times$ occupation pair specific effects (row 6); and about 8 percentage points (row 7) when we focus on job movers transiting between the same occupations *and* locations of origin and destination.

Intra-group mobility and group diversification – In Table 2, we study in a regression framework whether the heterogeneity in firm-level excess probabilities relates to group diversification. Controlling for firm- and group-level time-varying confounders, time dummies and firm $\times$ group fixed effects, we find that *diversification both across industries and across geographical areas is associated with more intense propensity to hire internally.*[12] Note that a priori diversification may affect the the propensity to hire internally in two opposite ways. On the one hand, it allows group units to be exposed to unrelated sectoral or geographical shocks, thus creating more scope for workforce reallocation across units. 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 industry-specific skills, trade union resistance, or labor market regulation. Our descriptive evidence in this section suggests that *on average* the former effect prevails. The analysis in Section 5.2 will allow us to go beyond this average result and show that, when an affiliated firm is hit by an *industry shock*, its ability to take advantage of the ILM and swiftly adjust its labor force is best served by a mix of industry diversification and geographical concentration.

While our descriptive evidence suggest that French business groups operate ILMs, so far we remained agnostic on whether ILMs are *special*, i.e. labor adjustments encounter less frictions when performed within internal as opposed to external markets. In the rest of the paper, we aim to identify this *ILM effect*, guided by the model we set up next.

probability disproportionately reflects the limited propensity to hire internally for these occupations.

[12]The effect of diversification is sizeable: for example, in a group of average size, a one-standard deviation increase in (4-digit) industry diversification (see Appendix Table A4) boosts the propensity to hire internally by 0.0081 (= 0.27×0.03, see column 4 of Table 2) 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 the propensity to hire internally equals 0.0246 percentage points, which represents as much as 27% of the average excess probability.

3 ILM Use in Response to Shocks: A Model

We lay out a model of optimal human capital allocation within a business group, where one affiliate is subject to a positive idiosyncratic shock. The aim is to understand how labor adjustment takes place following the shock, under the assumption that the ILM is less frictional than the external labor market.

A business group consists of two affiliates, A and B. Each unit i ($i = A, B$) produces using labor only, with production function $Y_i = \theta_i f(L_i)$ satisfying $f' > 0$, $f'' < 0$, where θ_i is a parameter capturing total factor productivity. Without loss of generality we also assume that $\lim_{L \to 0} f'(L) \to \infty$. Firms are price and wage takers; the price for affiliate i's product is p_i and the wage is w. We denote affiliate i's initial stock of labor as L_{0i}. Suppose that affiliate A is hit by a positive shock whereas affiliate B is not. Following the realization of the shock, the price of the good produced by affiliate A is $p_A + \varepsilon$, with $\varepsilon \in (0, +\infty)$. We model the shock as a demand shock; a productivity shock would lead to the same results as long as it calls for labor adjustment. The price and productivity of affiliate B are unchanged.

The group's headquarters has control over labor adjustment decisions in the group's units. Following the shock, it can expand the affiliate's labor force by an amount e_i using the external labor market (ELM), and in doing so it faces hiring costs.[13] We assume linear hiring costs $C(e_i) = He_i$ but results generalize to the case of non-linear adjustment costs.

The headquarters can also adjust labor using the internal labor market (ILM), moving workers across units. We denote with i the flow of workers reallocated from unit B to unit A. Not all the workers employed in other group affiliates are suitable to fill the vacancies in the positively shocked unit, for instance because of skill compatibility issues. Moreover, the suitable workers might reside outside of the shocked unit's commuting zone. We capture this idea assuming that only a fraction $\mu \in [0, 1]$ of affiliate B's existing stock of workers can be redeployed to A.

We assume that while hiring on the external market is costly, hiring workers from the available internal pool μL_{0B} only entails an infinitesimally small cost.[14] This assumption captures the fact that

[13] Labor market frictions in our model include, but are not limited to, direct hiring costs. Several papers have estimated that in many economies hiring costs amount to a non negligible fraction of the wage bill. 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. These papers only focus on recruitment and training costs, while ignoring indirect hiring costs that are more difficult to measure, i.e. costs borne because a vacancy is filled with an imperfect match due to asymmetric information, or the the cost of having unused capital when there is an unfilled vacancy as highlighted by Manning (2011).

[14] The assumption that internal adjustments entail an infinitesimally small cost is an innocuous normalization: what matters for the results is that internal adjustments are less costly than external ones. A non-null cost of internal adjustments allows to rule out a multiplicity of equilibria in which unit B hires workers on the external market and redeploys them to the positively shocked unit (this will be dominated by having A hire directly on the external market,

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 from lower information asymmetry concerning workers' talents (Greenwald (1986) and Jaeger (2016)), and may perform better than the external labor market in swiftly matching a vacancy with the right worker. Furthermore, training costs are lower for workers absorbed from the ILM whenever there is a group-specific human capital component. Internal and external "labor market partners" are otherwise identical.

The headquarters choose $e_A \geq 0$, $e_B \geq 0$ and i so as to maximize the total group value, subject to the ILM constraint. It thus solves:

$$\begin{aligned}\max_{e_A,e_B,i} \quad & (p_A+\varepsilon)\theta_A f(L_{0A}+e_A+i) - w(L_{0A}+e_A+i) - He_A + \\ & + p_B\theta_B f(L_{0B}+e_B-i) - w(L_{0B}+e_B-i) - He_B \\ & s.t. \quad i \leq \mu L_{0B}+e_B\end{aligned}$$

Defining λ as the Lagrange multiplier associated to the ILM constraint, the Kuhn-Tucker conditions are:

$$\frac{\partial V}{\partial e_A} = \begin{cases} (p_A+\varepsilon)\theta_A f'(L_{0A}+e_A^*+i^*) = w+H & \text{if } e_A^* > 0 \\ (p_A+\varepsilon)\theta_A f'(L_{0A}+i^*) \leq w+H & \text{if } e_A^* = 0 \end{cases} \tag{2a}$$

$$\frac{\partial V}{\partial i} = (p_A+\varepsilon)\theta_A f'(L_{0A}+e_A^*+i^*) - p_B\theta_B f'(L_{0B}-i^*) - \lambda = 0 \tag{2b}$$

$$\frac{\partial V}{\partial \lambda} = \mu L_{0B} - i^* \geq 0 \tag{2c}$$

$$\lambda \geq 0 \qquad \lambda[\mu L_{0B} - i^*] = 0 \tag{2d}$$

A formal solution of the model is provided in Appendix A.3. By equation (2b), the optimal ILM response i^* trades off the benefit enjoyed by the shocked unit A with the cost borne by unit B providing the workers. The headquarters may also resort to the external market ($e_A^* \geq 0$), depending on the thickness of the ILM (μ) and the size of the shock ε.

Result 1: *There is a pecking order of labor sources: after a positive shock to growth opportunities, unit A relies as much as possible on the ILM channel ($i^* > 0$,$\forall\varepsilon > 0$ and $\forall\mu > 0$) and only as a last resort it hires on the external labor market ($e_A^* > 0$ iff ε is large enough).*

In Appendix A.3 we also show that, depending on the size of the ILM access μ, the following two regimes arise:

hence $e_B = 0$ at the optimum).

Thick ILM (μ large) – The constraint $i \leq \mu L_{0B}$ is slack ($\lambda = 0$), regardless of the magnitude of the shock. By equation (2b), the headquarters reallocate workers from B to A ($i^* > 0$) up to the point where the marginal revenue product of labor ($MRPL_i$) is equalized across the two units. Only when the shock ε is very large, the headquarters also resorts to external hiring: the marginal revenue product of labor is equalized to $w + H$, and hence $e_A^* > 0$.

Thin ILM (μ small) – Unless the shock ε is very small, the constraint $i \leq \mu L_{0B}$ binds, hence $i^* = \mu L_{0B}$. Again, if ε is large, $e_A^* > 0$ is required to fully accommodate the shock. With the ILM constraint binding, the marginal revenue product of labor cannot be equalized across the two units: by equation (2b), there is a wedge $\lambda > 0$ between $MRPL_A$ and $MRPL_B$, capturing the misallocation of workers within the group due to the constraint on ILM activity. Differently from wedges in the misallocation literature (see Hsieh and Klenow (2009)), λ does not measure misallocation of factors across firms in the economy, but rather across firms within the same organization. The wedge λ also measures the *marginal value of the ILM*, i.e. the increase in group profits when the constraint is relaxed (i.e. μL_{0B} increases) and one additional group worker can be redeployed to the shocked unit.[15] Figure 1 (left hand panel) illustrates this case, showing that $\partial\lambda/\partial\mu < 0$: *the marginal value of the ILM is larger when access to the ILM is more constrained.*

In Figure 1 (right panel), the shaded green area shows the total value generated by the ILM, i.e. the loss in group profits if access to the ILM was shut down in a group subject to a positive shock. In the case represented in the figure, a firm that cannot access the ILM (i.e. with $\mu = 0$) hires workers on the external market: this adjustment corresponds to the $MRPL_A$ locus shifting down (dotted line) until $MRPL_A = w + H$ at $i = 0$. By contrast, a firm enjoying ILM access relies on internal hiring as much as possible, setting $i^* = \mu L_{0B}$. The figure shows that the availability of the internal channel generates value in two ways. First, hiring from the external market is substituted by cheaper internal hiring, thereby saving on adjustment costs. Second, if its ILM access is large enough the shocked firm is *also* able to adjust more than the fully constrained firm, taking better advantage of the growth opportunity.[16] This is summarized in the following result.

Result 2: *When unit A has more access to the ILM, unit A's total employment and the net group value increase more in response to the shock*

To account for the heterogeneity of affiliates within the group, in the Appendix we extend the

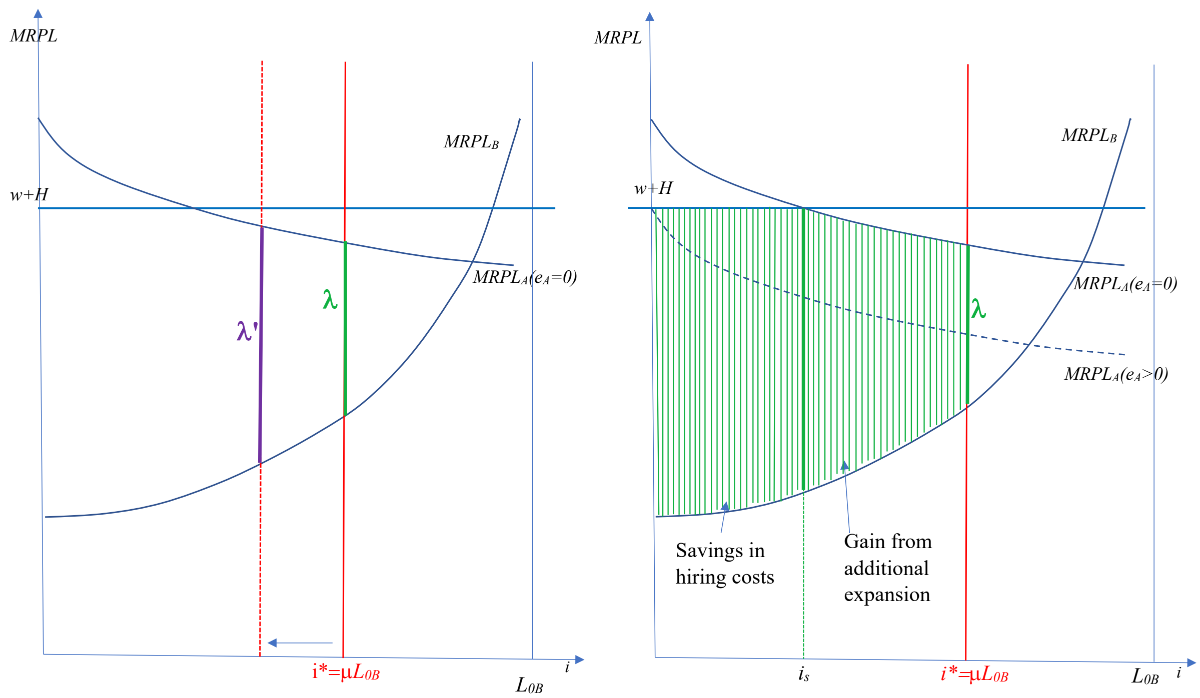
[15] More precisely, λ equals the increase in profits in the shocked unit due to the additional worker absorbed internally ($MRPL_A - w$), net of the profit reduction in unit B due to the loss of one worker ($MRPL_B - w$).

[16] In a dynamic model, Fajgelbaum (2020) shows how frictions to job-to-job mobility adversely affect firm growth and the timing of export entry. While our model is static and all adjustment takes place when the shock occurs, our empirical approach allows us to have an insight into how firms with high ILM access can react swiftly to growth opportunities.

model to include three BG units (results can be generalized to $n \geq 3$ units). Unit A is hit by the shock, while units B and C are not. The bilateral ILM flows from unit B and C, respectively, to unit A, cannot be larger than the workforce redeployable to A: $i_{AB} \leq \mu_B L_{0B}$ and $i_{AC} \leq \mu_C L_{0C}$. Subject to these two constraints, and similarly to the two-unit model, the optimal ILM allocation aims to minimize the wedge between marginal revenue products of labor of shocked and non-shocked units. This implies that ceteris paribus, unit A draws workers first from its least productive affiliate.

Result 3: *Holding constant across affiliates the pool of redeployable workers ($\mu_B L_{0B} = \mu_C L_{0C}$), the ILM flow to unit A from the less productive affiliate is larger: $p_B\theta_B > p_C\theta_C$ implies $i^*_{AC} > i^*_{AB} \geq 0$.*

Figure 1: Optimal ILM adjustment and the value of the ILM



Note: in both panels, the horizontal axis measures the ILM flow from unit B to unit A, the vertical axis displays the marginal revenue product of labor ($MRPL$). The blue curves represent the $MRPL$ of the two units as a function of internal hiring i, after the shock has hit unit A. The left hand panel illustrates the optimal ILM allocation when the ILM constraint binds. The ILM allocation that satisfies $i^* = \mu L_{0B}$ is such that $MRPL_A < w + H$, implying $e^*_A = 0$ by condition (2a). Condition (2b) defines the wedge λ between $MRPL_A$ and $MRPL_B$ at the optimum. A decrease in ILM Access μL_{0B} translates into a higher λ. In the right hand panel, the shaded green area represents the net group value generated by ILM Access $\mu L_{0B} > 0$, compared to no ILM Access ($\mu L_{0B} = 0$). When $\mu = 0$, external hiring takes place, shifting $MRPL_A$ downward (dotted line) until $(p_A + \varepsilon)\theta_A f'_A(L_{0A} + e^*_A) = w + H$, satisfying condition (2a). By contrast, with ILM Access $\mu L_{0B} > 0$, external hiring does not take place as $(p_A + \varepsilon)\theta_A f'_A(L_{0A} + \mu L_{0B}) < w + H$. The level of internal hiring i_s indicated in the figure satisfies $MRPL_A(i_s) = w + H$. Hence, at $i = i_s$, unit A performs the same labor adjustment as an otherwise identical firm with no ILM access, yet by resorting to cheaper internal hiring, it saves on adjustment costs Hi_s: this is a first source of value. In addition, the availability of the internal channel allows unit A to adjust its workforce by an additional $\mu L_{0B} - i_s$, and thus expand more than a firm with no ILM access, a second source of value.

4 Empirical Design

Our model posits that ILMs are "special" in the sense that firms seeking to expand their labor force encounter less frictions when drawing workers from their ILM – the group affiliates – rather than the external labor market. This has two major implications. First, BG firms have a pecking order of labor resources: when responding to positive shocks to growth opportunities, they disproportionately rely on their group's ILM rather than on the external labor market (*Result 1*). Second, BG firms with better access to the ILM expand more in the face of positive shocks (*Result 2*). In subsections 4.1 and 4.2, we discuss the empirical challenges we face in testing these predictions, and in using our empirical findings as evidence that ILMs are less frictional labor adjustment channels. Subsection 4.3 explains instead how we test *Result 3* that shocked BG firms draw workers first from less productive affiliates.

Our empirical analysis exploits positive shocks to growth opportunities, generated by the collapse of BG firms' large product market competitors. In subsection 4.4 we describe how we identify 100 large closure events that occurred between 2002 and 2010 in 84 French industries; we then argue that these opened up expansion opportunities for BG firms in the affected industries.

4.1 Is there a pecking order of labor sources in the face of positive shocks?

Consider a sample of BG firms j, each having a given number of labor market partners (i.e. firms to potentially absorb workers from), some of which are part of the same group. Labor market partners affiliated with the same group as j are referred to as "internal partners", whereas the others are "external partners". We aim to establish whether, in response to a positive shock, BG firm j disproportionately increases its hiring from internal partners (as opposed to external partners) because its ILM faces milder frictions.

In the *ideal experiment for our analysis of positive shocks*, for a given unit of observation (the firm that is hit by a shock), *the same-group status of firm j's partners is randomly allocated.* Hence, internal and external partners are, on average, identical. As soon as all firms have reached a stationary situation (in particular, the labor flows between the destination firm j and its partners are stationary, with all idiosyncratic shocks zeroed out over time), it becomes possible to examine the effects of a positive idiosyncratic shock hitting firm j at time t_0. In this setting, a pre/post shock comparison of the (average) share of internal hires is enough to understand whether j disproportionately relies on internal hires in response to the shock, and claim that this response is due to the ILM channel being less frictional.[17]

However, affiliation to a group is obviously not randomly allocated. Hence, external and internal partners are likely to differ in terms of observable as well as unobservable characteristics, which will differentially affect the intensity of internal vs external labor market flows. For instance, internal partners (but not external partners) may employ workers endowed with skills highly reusable in firm j; if hiring from a firm employing workers with reusable skills is easier, the preference for internal hiring would not be due to the ILM being less frictional.

In addition, the group's structure may vary over time. For example, following the shock a group may acquire an external partner from which it used to hire many workers. As a consequence, a simple pre/post shock comparison of the (average) share of internal over total hires of firm j would no longer identify the *ILM effect*, as it would be confounded by the changing composition of the set of firms of origin.

To address these issues, we proceed as follows. We consider all BG-affiliated firms that operate in the shocked industries. For each shocked firm j, we identify labor market partners as the set of firms that, in at least one year, have been the origin of at least one employee hired by firm j. We fix the group each firm (of origin and of destination) belongs to, using the affiliation status one year before the shock. Hence, whether a labor market partner of firm j is internal or external is a fixed characteristic. This implies that firm fixed effects control for all time-invariant characteristics, both of the destination firm and of the group it belongs to, that may differentially affect the intensity of internal vs. external hiring, including the characteristics of the set of firms of origin.

We exploit the staggered nature of our large closure events and implement a pooled event study. We denote as 0 the year of the shock, i.e. the first year in which the large competitor is no longer active in a given industry, and build a three-year window around the event. Following the design of Cengiz, Dube, Lindner, and Zipperer (2019), we estimate the following equation:

$$y_{j(s)t} = \phi_{j(s)} + \beta_t + \sum_{\tau=-3}^{3} \alpha_\tau I_{\tau st} + \varepsilon_{j(s)t} \tag{3}$$

where $y_{j(s)t}$ denotes the share of internal hires (as well as other firm outcomes) observed for firm j that operates in shocked sector s at time t. If there are multiple units in a group operating in the same shocked industry, we consider them as one shocked firm j, adding up their hires, employment,

[17] If BG affiliation was randomly allocated, one could identify not only whether the ILM is activated *in response to shocks*, as we study here, but also the *ILM effect in a stationary situation*. However, outside this ideal setting, the presence of unobservable factors undermines identification of the *ILM effect* in "normal times". We have discussed this issue in Section 2.3, where we provide some descriptive evidence on ILM activity in "normal times", accounting for some observable factors.

investment, market shares. The treatment indicator $I_{\tau st}$ equals 1 if year t is τ years away from the shock in industry s. The specification also includes calendar year indicators β_t. The term $\phi_{j(s)}$ is a firm-fixed effect. In this context, the *ILM effect* is identified out of the within-firm time variation. We cluster standard errors by industry, which is the level at which the shock takes place, and (destination) group, so as to account both for within-industry correlation of the error term across firms, and for within-group correlation of the error term across industries.

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

We acknowledge that the firm fixed effect in equation (3) is no cure-all. In particular, it cannot account for firm-specific time-varying factors that differentially affect the response of internal and external hires to the shock. For instance, the positive shock may *change* the hiring behavior of firms, making them more inclined to hire workers with a specific characteristic which happens to be abundant among same-group firms. In this case, one would observe an increase in internal hires due not to the *ILM effect* but rather to the change in hiring policy.[18] We refer to the pair-level analysis presented in Section 5.3 to mitigate, at least partially, this concern. There, we look at the evolution of internal flows in pairs of firms where both internal and external partners are all located in the same local labor market as the shocked firm, to see if shocked firms still favor the internal channel for hiring. We would not observe such preference if the shock had spurred a change in the hiring policy of BG firms, making them more inclined to hire locally.

4.2 Does the ILM allow BG firms to better take advantage of positive shocks?

After investigating whether BG firms increase their use of ILMs after a positive shock to growth opportunities, we want to test the prediction that the ILM favors growth in the aftermath of the shock. To this aim, a comparison between the expansion of BG versus stand-alone firms would not be appropriate, because any excess growth observed in BG firms might also be ascribed to their other

[18]This mechanism may generate a bias even if the underlying characteristic, upon which the change in the hiring policy is based, is fixed. That is, even though abundance of redeployable workers in the rest of the group is a fixed firm characteristic, if the shock alters how redeployability affects the propensity to hire from a specific partner *and* internal partners are more redeployable, a bias arises even controlling for firm fixed effects.

unique features, among which the ability to rely on the Internal Capital Market (ICM).

Our approach is thus to focus on BG firms, and compare the evolution of outcomes across those that enjoy different levels of access to the ILM (μ in our model). The geographical distance between group units is plausibly one key determinant of *ILM Access*. First, in most employment systems including France, a relocation across different sites is more likely to be challenged/refused by a worker when it falls beyond a reasonable commuting distance from the current site.[19] 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.[20] Fixing *ILM Access* at $\tau = -1$ makes sure that it is not influenced by the shock. We study the evolution of outcomes in shocked BG firms with different levels of *ILM Access* by estimating:

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

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* (that is, *ILM Access* above median; in the top quartile; top decile; top 5 percent of the distribution in the sample of shocked BG firms). The term $I_{\tau j(s)t}^L$ does the same for firms enjoying *ILM Access* strictly below median (i.e. no same-BG workers within the same local labor market). 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, as 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 $\tau = -1$. Standard errors are again clustered both by industry and by group.

In an ideal experiment, BG firms with different levels of access to the ILM are identical in all other respects. Of course, this is not necessarily the case. In particular, *ILM Access* might be correlated with characteristics of the shocked firms, of their group and of their set of external partners that

[19] 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 requesting the transferability of the worker's seniority across firms) makes the transfer possible without it being considered a dismissal. See http://www.magazine-decideurs.com/news/la-mobilite-du-salarie-au-sein-d-un-groupe.

[20] France is partitioned into 348 local labor markets ("zones d'emploi" or ZEMP) based on commuting data collected by the INSEE. French courts often rely on the ZEMP concept in labor litigations, to establish whether a relocation falls beyond a reasonable distance from the original employment site.

affect the way firms react to shocks. We acknowledge that this could undermine our identification strategy. While we cannot control for all these factors, we address two major concerns that arise in this respect.

First, firms with higher *ILM Access* may also be located within a thicker local external labor market: in this case, which channel allows firms to expand after the shock would be unclear. In Section 5.2, we document that the share of internal hires increases with *ILM Access*, something that we would not expect to see if *ILM Access* was simply capturing external labor market access. Second, BG firms with high *ILM Access* may belong to groups that also have more scope for using the ICM in response to a positive shock, e.g. due to industry diversification. In Section 5.2 we provide evidence suggesting that the ICM is not driving the differential response to the shock documented in this paper.

4.3 Do shocked BG firms draw more workers from less productive affiliates?

Our next step is to dig deeper into the ILM mechanism and test our model prediction that ILM flows in response to a shock vary with the characteristics of the origin-firm. To this aim, we exploit the granularity of our data and study employment flows between *pairs of firms*: in section 5.3, our unit of observation is no longer a shocked firm j, but a pair of firms jk in a given year, in which the destination j is a shocked BG-firm and the origin k is a labor market partner from which the shocked firm may hire workers.

We compute the bilateral employment flows (either positive or equal to zero) within each pair jk in each year, and adopt an event study approach to estimate the differential reaction of internal and external flows to the shock:

$$f_{j(s)kt} = \phi_{j(s)k} + \beta_t^{Int} + \beta_t^{Ext} + \sum_{\tau=-3}^{3} \alpha_\tau^{Int} I_{\tau st}^{Int} + \sum_{\tau=-3}^{+3} \alpha_\tau^{Ext} I_{\tau st}^{Ext} + \varepsilon_{j(s)kt} \tag{5}$$

where $f_{j(s)kt}$ is the ratio of workers hired by BG-affiliated firm j (active in shocked industry s) from firm k in year t, to the total number of firm-to-firm movers hired by firm j in year t. The treatment indicators for internal and external flows, $I_{\tau st}^{Int}$ and $I_{\tau st}^{Ext}$, equal 1 if year t is τ years away from the shock in industry s. We allow for different aggregate cyclicality of internal and external flows adding separate sets of calendar year dummies β_t^{Int} and β_t^{Ext}. We cluster standard errors by industry and (destination) group. The term $\phi_{j(s)k}$ is a pair fixed effect that controls for all time-invariant unobservable *pair* characteristics (including the time-invariant unobservable characteristics of the group) that may differentially affect the response of internal and external hires to the shock.[21] The DiD estimates $\hat{\alpha}^{Int}_{\tau} - \hat{\alpha}^{Int}_{-1}$ and $\hat{\alpha}^{Ext}_{\tau} - \hat{\alpha}^{Ext}_{-1}$ measure the change, with respect to -1, in the fraction of hires from the typical internal and external partners τ years away from the event, relative to the counterfactual.

The analysis of bilateral flows allows to investigate whether the effect of the shock is heterogeneous across pairs, in line with *Result 3* of the model: we expect shocked firms to disproportionately hire from less productive firms within the group. We test this prediction by *allowing for the effect of the shock in equation* (5) *to differ as a function of observable characteristics of the pair $j(s)k$ (in particular, of the firm of origin k).*

The introduction of the pair-fixed effect implies that we do not exploit the cross-sectional variation between internal and external pairs. This would be a valuable source of variation in a world in which BG firms hire more on the internal market *only* because of lower frictions. In this context, the presence of pair fixed effects would not be desirable, as it would kill variation informative of the effect of the differential frictions on the internal vs. external labor markets, even in the absence of the shock (i.e. in normal times). However, BG firms are likely to hire more on the internal market (also) because of the (self-)sorting process of firms into groups. This makes internal partners different from external ones along various dimensions that will affect the propensity to hire internally vs externally. Therefore, the difference between the *levels* of internal and external flows in normal times cannot be attributed only to differential frictions. Summing up, adding pair fixed effects has the cost of preventing us from identifying the (uninformative) difference between the *levels* of internal and external flows, but has the advantage of allowing us to identify the (dynamic) reaction of internal and external flows to the shock controlling for systematic pair characteristics.

4.4 Large closures as positive shocks to growth opportunities

To conduct our empirical analysis in Section 5, we exploit the closures of large competitors, which we regard as positive shocks to growth opportunities for the remaining firms in the industry.

First, we identify closures that occurred across various industries in France between 2002 and 2010: a "closure" is any episode in which a firm experiences an employment drop of 90% or more over one year during our sample period. In order to eliminate false closures, i.e. situations in which firms simply change identifier relabelling a continuing activity (such as in the case of an acquisition),

[21] In a context in which the composition of the set of firms of origin is constant over time, firm fixed effects in equation (3) fully control for the characteristics of the firms of origin. Pair fixed effects are, instead, a valuable addition with respect to firms fixed effects whenever the composition of the set of firms of origin is time-varying. In our case where we fix the BG status of firms just before the shock, the composition of the set of firms of origin may still vary due to firms of origin entering and exiting the market. This is an advantage of the pair-level approach.

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. The closure rates that we find (see Table A7 in Appendix A.4), their evolution over time and their heterogeneity across firms of different size are consistent with an extensive study from INSEE on closures in the French economy (Royer (2011)).

Second, we focus on the closures of large firms, which we define as firms with more than 500 workers – on average – in normal times, i.e. at least 4 years prior to the closure event. We conduct our analysis on the 84 industries that experience either a single large closure or multiple closures occurring in the same year, accounting for 100 large closure events in total. Table A8 in Appendix A.4.2 lists these shocked industries, reporting the closure year and the size of the closing firm in normal times.

A priori, the closure of a large competitor is not necessarily a positive shock for the surviving firms in the industry. On the positive side, a closure event creates a growth opportunity for other firms by increasing demand for their products. On the negative side, those operating in the same geographical area as the exiting competitor may be harmed by negative local spillovers as documented by Gathmann, Helm, and Schönberg (2020); however, this channel is unlikely to play a role here, as only 3% of the shocked BG firms in our sample have a closing competitor that was active in their local labor market. The evidence we present in Section 5.1 on the evolution of firms' outcomes suggests that the positive effect dominates for the shocked BG firms included in our sample.

An important concern is that large competitors may be driven out of the market *because* of expanding BG firms operating in the same industry. If this was the case, one would observe an expansion of BG firms in the years preceding the closure event, translating into substantial pre-trends in the empirical analysis. The absence of such pre-trends in the results we present below alleviates this concern.

5 BG Firms' Response to Positive Shocks

We now test the predictions of our model, relying on the methodology detailed in Section 4.

5.1 Reliance on the ILM in response to the shock

We observe 97,836 firms active in our shocked industries, out of which 90,973 are stand-alone firms and 6,863 are BG firms, affiliated with 6,187 different groups (shocked firms active in different industries may belong to the same group). Hence, BG firms represent 7% of all firms active in shocked industries, but account for 48.9% of total employment in their industry and 52.34% of total sales, in line with the figures reported in Section 2.2 on the presence of business groups in France.

As explained in Section 4, our analysis focuses on the 6,863 BG-affiliated shocked firms, which give rise to 51,632 firm-year observations. Table A9 reports descriptive statistics of the shocked firms and the groups they are affiliated with. The Table confirms that the distribution of groups is very skewed, with few large and diversified groups coexisting with many smaller, more focused groups.

We estimate equation (3) on this regression sample. As a first step we look at employment, hiring, investment and market share, to confirm whether BG firms expand following the closure of a large competitor. Figures 4 report the estimated $\widehat{\alpha}_\tau - \widehat{\alpha}_{-1}$ together with 95% confidence bands. Panel (a) shows that after the shock, employment increases on average by 10 units with respect to event date -1, an evolution mirrored by the evolution of hiring in Panel (b). Although estimates are somewhat imprecise, Panel (c) suggests that the average investment in shocked BG firms also increases at $\tau = +1$ and $+2$. Consistently with the expansion in employment and capital, panel (d) shows that BG firms take advantage of the collapse of a large competitor and increase their market share by about 0.06 percentage points, an 8.5% increase with respect to an average pre-event market share of 0.7%. The evolution of these outcomes suggests that the closure of a large competitor represents a positive shock to growth opportunity for BG firms. The absence of pre-trends suggests that the growth of BG firms is unlikely to be the cause of competitor closures.

We then turn to the central issue: *do BG firms have a pecking order of labor sources, turning first to the ILM as a channel to adjust?* To answer this question, we study the evolution of the share of internal hiring over total hiring (Figure 5): this increases by 0.01 at $\tau = +1$ and by 0.015 at $\tau = +2$, a 17% and 26% rise relative to the share of internal hires the year before the shock (which equals 0.057). This result suggests that affiliated firms prefer to rely on ILM hiring when responding to a positive shock, in line with *Result 1* in the model.

In light of the recent literature on TWFE estimators, in Appendix A.5 we assess the robustness of our main results using the "interaction-weighted" estimator proposed by Sun and Abraham (2021), that is specifically devised for event study designs like ours with binary treatment and different treatment timing across cohorts. de Chaisemartin and D'Haultfœuille (2020) propose an alternative estimator designed for a staggered binary rollout setting, ruling out dynamic effects. We present additional robustness based on a recent adaptation of their estimator that allows for dynamic effects (see de Chaisemartin and D'Haultfœuille (2021)). Appendix A.5 discusses these estimators in greater detail. With the Sun and Abraham (2021) estimator, we obtain very similar results for all outcomes, in terms of direction of the effects, significance and magnitude. With the de Chaisemartin and

D'Haultfœuille (2020) estimator, the robustness is less clear-cut. Results are confirmed for the share of internal hires; for employment, the point estimates at $\tau = 0$ and $\tau = +1$ are positive but not significant; for market share, we only see a significant increase at $\tau = 0$.

5.2 Firms with better ILM access take more advantage of positive shocks

We now turn to our second research question: *do BG firms with better access to their group's ILM expand more in the aftermath of a shock?*. To test this prediction, we estimate equation (4) and compare the evolution of outcomes in shocked BG firms that enjoy different levels of access to their group's human capital, using our exogenous measure of *ILM Access*.

As median *ILM Access* for shocked BG firms is equal to 1 worker, BG firms with below-median *ILM Access* are constrained in their ability to draw on their group's human capital in response to the positive shock. Hence, from an ILM perspective only, they are very similar to stand-alone firms. As expected, *ILM Access* translates into ILM usage: firms with access to the ILM increase their share of internal hires in the aftermath of the shock by 0.019 (a 21% increase w.r.t the pre-event baseline) at $\tau = +1$ and 0.024 (a 26% increase w.r.t the pre-event baseline) at $\tau = +2$, while firms with no access to the ILM do not (Figure 6(a)). We also explore the extensive margin of ILM use: Figure 6(b) shows that in response to the shock, BG firms with above-median *ILM Access* increase the number of *active* ILM partners (i.e. they expand the set of affiliates from which they actually hire workers) by 12.5% relative to the baseline. Table A11 in Appendix A.4 reports average pre-event outcomes by *ILM Access*. (See Appendix A.5 for a robustness assessment of the results presented in this section to the use of the alternative estimators proposed by Sun and Abraham (2021) and de Chaisemartin and D'Haultfœuille (2021).)

In Figure 7, we study the evolution of employment. Panel (a) shows that firms with strictly below-median *ILM Access* do not adjust their workforce in response to the shock, whereas firms with above-median *ILM Access* do expand employment after the event. The other panels suggest that the expansion of employment is more pronounced the larger the *ILM Access*. In a similar way, Figure 8 shows that while firms with below-median *ILM Access* do not increase their capital expenditures after the shock, firms with high *ILM Access* do so one year after the shock, with the effect mostly visible among firms in the top decile of the distribution.

Figure 9 suggests that there is a strong positive relationship between *ILM Access* and BG firms' market share growth after the shock: the shock has no effect on the market shares of firms with no (i.e., below-median) *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). The effect increases with the intensity of *ILM Access* when moving from panel (a) to panel (d) of Figure 9 and is sizeable. For instance, 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. 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. The effect is even more important for firms in the top 5 percent of the *ILM Access* distribution (panel d).

The results in this Section suggest that geographical proximity to the group's workforce (the key component of our *ILM Access* measure) is central to BG firms' expansion and performance. However, to the extent that BG firms can rely on both the group's ILM and its Internal Capital Market, we also ask whether their post-shock expansion is driven by a combination of ILM and ICM factors. Therefore, we study whether growth in employment and market share is more pronounced when shocked firms are affiliated with groups that are more diversified across industries. This is because industry diversification exposes group units to idiosyncratic shocks and creates room for redeploying both workers *and* capital towards units in the shocked industry. Figure 10 indicates that shocked units' growth is not significantly larger in more diversified groups. In sum, *affiliation with a sectorally diversified group does not appear to drive BG firms' growth unless paired with geographical proximity to the group's human capital.*

We also explore whether the ICM is a necessary complement to the ILM, by asking whether shocked BG units with above median *ILM Access* expand more when they can also draw on a "deep pocketed" ICM (which we proxy with rest-of-the-group cash holdings). The results in Figure 10 suggest that this is not the case, at least when group cash is used as a measure of ICM access.[22]

5.2.1 Value of the ILM and group characteristics

We have just shown that in the years following the shock, BG firms with below-median *ILM Access* do not increase reliance on the ILM, and do not expand their workforce, investment, market shares. Differently to their high-*ILM Access* counterparts, they fail to exploit a growth opportunity. How much value would be created if the ILM constraint was relaxed for these firms, allowing them to draw workers from their non-shocked affiliates? We attempt a model-based quantification to complement our empirical analysis and further our understanding of how the structure of groups affects their

[22]While we can use worker flows to measure ILM activity, we do not have data on internal capital flows between group subsidiaries, to track ICM activity. Instead, we use as a proxy for ICM access the total cash holdings held by all subsidiaries affiliated with a BG firm: in previous work, these has been shown to affect BG firms' outcomes (Boutin, Cestone, Fumagalli, Pica, and Serrano-Velarde (2013)).

potential to benefit from the ILM.

In our static model, the ability to redeploy one additional worker from the non-shocked to the shocked unit generates a marginal increase in group profits equal to the wedge λ, which in fact measures *within-group labor misallocation* due to constrained *ILM Access*. We focus on shocked BG firms with below-median *ILM Access* and, using equation (2b), we calculate λ as the difference at $\tau = +1$ (the first year after the shock) between the marginal revenue productivity of labor (MRPL) of the shocked unit and the MRPL of the least productive affiliate active in *non-shocked* industries. We assume a Cobb-Douglas production function, with MRPL proportional to Value Added per Worker and a proportionality factor equal to the labor share.

In Table 3 we report the average value of the ILM wedge λ, alongside group/firm characteristics. We do so for shocked firms with above- vs below-median group industry diversification: λ is larger in more diversified groups, that are more exposed to idiosyncratic shocks and thus have more potential for labor reallocation across low-MRPL and high-MRPL firms. The net increase in one-year group profits that would be generated by the reallocation of *one extra worker* ranges from 124,000 euros (assuming a labor share = 1/2) to $165,000$ euros (assuming a labor share = 2/3), much larger than the wedge in less diversified groups.[23]

We compare these figures to the consolidated group profits one year before the shock.[24] The ratio of λ to average group profits ranges between 0.002 and 0.003. In other words, our calculations indicate that *the ability to redeploy one worker via the ILM towards the shocked BG firm would boost consolidated group profits by* $0.2-0.3$ *percent.* To put things in perspective, we compare this effect to the contribution of top employees to firm performance, which has been estimated exploiting data on CEO deaths and hospitalizations. Bennedsen, Perez Gonzalez, and Wolfenzon (2020) show that operating profits over assets decline by 1.7% following a CEO's death, while lengthy hospitalizations cause a 0.9% decline. The effect of hospitalizations of non-CEO top executives is half this size, suggesting that the contribution to firm performance is substantially larger for CEOs than for other top executives.[25] Bertrand and Schoar (2003) find similar magnitudes when looking at the role of manager fixed effects in explaining firm performance. Unsurprisingly, the internal reallocation of one

[23] While the macro-level labor share is around 2/3, firm-level shares are likely lower due to the presence of intermediate inputs. As there is no consensus in the literature on how to measure the labor share at the firm level (see e.g. Saumik and Hironobu (2019)), we took the conservative approach to use 1/2 as a lower bound (in line with Saumik and Hironobu (2019) recent evidence for medium/large firms in advanced economies).

[24] In a non-negligible number of cases, consolidated group profits are close to zero, driving up remarkably the ratio between λ and group profits. Therefore, we prefer to be conservative and compare the average value of λ to the average consolidated group profits reported for the firms in columns 1 and 2 of Table 3.

[25] Nguyen and Nielsen (2014) find an average negative (-1.22%) stock price reaction to the sudden death of a CEO. Salas (2010) reports a positive stock market reaction to the death of "entrenched" CEOs, i.e. those with long tenure and poor past performance, but a negative (-1.8%) stock price reaction to the death of non-entrenched CEOs.

single average employee (i.e. not a top executive) has a smaller yet sizeable impact on consolidated group profits: our calculations suggest this ranges between 1/5 and 1/9 of the estimated impact on profits of a CEO's continued employment.

Why do sectorally diversified groups fail to exploit the ILM? What prevents them from efficiently reallocating workers from non-shocked to shocked units, failing to absorb such a large wedge between MRPLs? Our data indicates that these groups are also *geographically dispersed*: 91% of the employment in non-shocked affiliates is located in a different department (75% in a different region) than the shocked firm (Table 3).[26] This *geographical dispersion seems to generate intra-group labor misallocation*. This is in line with our model, where a smaller *ILM Access* (μ), due for instance to distance between shocked and non-shocked units, translates into a larger λ.

Our model-based quantification thus confirms the lesson we drew from this section's empirical findings: group structure is key to exploiting the benefits of the ILM. *Groups that are hit by industry shocks are better served by a combination of industry diversification (that makes the group more exposed to idiosyncratic industry shocks) and geographical focus (that facilitates the reallocation of workers across units).*

5.3 ILM worker flows between pairs of firms

We now turn to study the bilateral flows of workers between pairs of firms, as discussed in Section 4.3. We estimate equation (5) where the unit of observation is now a pair (firm of origin–destination firm) in a given year, in which the firm of destination is a BG 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 A18 in Appendix A.4).

Figure 11, panel (a), reports the estimated normalized coefficients for internal flows ($\widehat{\alpha}_{\tau}^{Int} - \widehat{\alpha}_{-1}^{Int}$), together with 95% confidence bands. Starting from $\tau = 0$, internal flows significantly increase relative to the year before the event. Given that average internal flows in the pre-event window amount to 7.4% (Table A19, Appendix A.4), on average the shock raises internal flows by about 6.8% at $\tau = 0$, about 15% at $\tau = +1$, and 20% at $\tau = +2$ and $\tau = +3$.[27] These results are robust to using the

[26] By contrast, Table 3 shows that groups that are less diversified across industries and thus less exposed to idiosyncratic shocks, have smaller gains to grasp from a relaxation of ILM constraints. While less geographically dispersed, they still face some hurdles reallocating workers internally, preventing them to completely absorb the internal wedge between MRPLs.

[27] While the share of internal hires does not increase at $\tau = +3$ (see Figure 5), the average bilateral ILM flow does. In our sample, all pairs of firms are observed both before and after the shock. However, in some pairs the firm of origin may exit from the sample because it shuts down, which may reduce the number of labor market partners in periods more distant from the shock. This may lead to an increase in the average bilateral flow at $\tau = +3$, as the total ILM inflow is distributed over a smaller number of ILM partners. This discrepancy suggests that groups may react to positive shocks hitting part of the organization by closing down some of their (arguably less productive) units. This is an interesting phenomenon that we believe is best left to future research.

alternative estimators proposed by Sun and Abraham (2021) and de Chaisemartin and D'Haultfœuille (2021) (Appendix A.5), and confirm what we learn in our firm-level analysis: group-affiliated firms increase their reliance on the ILM when responding to positive shocks to growth opportunities.

If groups are concentrated in one geographical area whereas external partners are more dispersed, the increase in the ILM flows that we observe might simply be due to the shocked firms hiring locally. To address this concern, we compare the evolution of flows within pair of firms where both internal and external partners are *all located in the same local labor market as the shocked unit.* Figure 11, panel (b), shows that even when labor market partners are all geographically close, affiliated firms still favor the internal channel for their hiring. This confirms that same-group affiliation is *per se* a factor facilitating labor mobility across firms. The result also mitigates the concern that the estimated increase in internal hiring may be due to the shock spurring a change in hiring policy, making the firm more inclined to hire locally.[28]

5.3.1 ILM response and the firm-of-origin characteristics

Which group member firms are likely to "provide" more employees to the ones benefiting from a positive shock? Our model predicts that a positively shocked unit should absorb more workers from less productive units (*Result 3*). 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, proxying productivity with Value Added Per Worker. Figure 12(a) shows that less productive group members contribute more workers to the group ILM after the shock. We then use pre-event capital expenditures (Capex) as a proxy for growth opportunities. Figure 12(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.

These results suggest that ILMs, by redeploying workers from less to more productive and promis-

[28]Given the industry nature of our shock, group sectoral concentration cannot be a driver of internal hiring in our empirical analysis. Indeed, our model predicts that shocked BG firms should not hire from same-group affiliates operating in their same industry (and therefore subject to the same shock). Table A21 in the Appendix (columns 7 and 8) provides evidence supporting this prediction. Instead, when we consider (internal and external) labor market partners all operating in a different 4-digit industry than the shocked firm, and thus not experiencing the same shock, we *do* observe an ILM response (but not an ELM response). See Table A21 (columns 5 and 6).

ing units, may affect the amount of labor misallocation across industries. They also suggest that shocked BG firms may grow more or less in response to the shock depending on the productivity of their affiliates, to the extent that this determines the scope for intra-group labor reallocation and thus the intensity of ILM flows. In Figure 13, we expand on the results on firm-level outcomes presented in Section 5.1 and look again at employment and market share expansion in shocked BG firms: we find that this is larger when other firms in the same group and the same local labor market have lower productivity.

5.3.2 ILM response and workers' occupation

We then ask whether a positive shock has heterogeneous effects across occupations, as these may be affected differently by hiring frictions that make the ILM valuable. We expand equation (5) measuring flows for different categories of workers and estimate:

$$f_{j(s)kot} = \phi_{j(s)ko} + \beta_t^{Int} + \beta_t^{Ext} + \sum_{o=1}^{4} \sum_{\tau=-3}^{+3} \alpha_{\tau,o}^{Int} I_{\tau st}^{Int} + \sum_{o=1}^{4} \sum_{\tau=-3}^{+3} \alpha_{\tau,o}^{Ext} I_{\tau st}^{Ext} + \varepsilon_{j(s)kot}, \tag{6}$$

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 14 (Table A24), we compare the ILM response across the four main occupational categories in the DADS (see Table A.1): managers/high skilled (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 and a slightly weaker response for clerical workers, while we do not observe a clear response for intermediate professions.

Relative to the year before the event, ILM hires 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 A19 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 similar increase (0.39 percentage points at $\tau = 0$, and 0.49 and 0.43 percentage points respectively at $\tau = 1, 2$), hence approximately a 20% increase with respect to the pre-event levels.[29]

To better understand what drives ILM flows, we analyze results based on a finer classification of occupations, using the technical skill content alongside the position in the firm hierarchy. In Table A25 we report the results for different types of managers and blue-collars. We observe a significant ILM response to competitors' closures for STEM-skilled managers/professionals and skilled blue-collar workers. Conversely, group firms do not increase the ILM hiring of administrative managers/professionals and unskilled blue-collar workers. This suggests that among the different components of human capital that the ILM helps reallocate, technical knowledge is more prominent than managerial practices.

Our findings suggest that group firms rely on the ILM primarily when hiring frictions on external markets are severe, as is the case for skilled workers (Abowd and Kramarz (2003), Kramarz and Michaud (2010), Blatter, Muehlemann, and Schenker (2012)). Because skilled/technical workers in both managerial and blue collar positions are likely to condition firm's growth, access to such workers through the ILM should represent a competitive edge in the face of positive shocks.[30]

6 Conclusion

Why are some organizations better able than others to exploit growth opportunities? Is access to skilled human capital central to growth? In this paper we address these questions by studying how some widespread organizations, namely business groups, respond to positive shocks to their growth opportunities using their Internal Labor Markets. To do so, 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, this paper is the first to show that organizations grow, build market share, and improve their performance using their ILM to accommodate positive shocks to the growth opportunities they face. This is compatible with a model where hiring frictions are eased when labor adjustment takes place within the ILM rather than using the external market. We also explore how group characteristics affect the value of the ILM: we show that when one of its business units is

[29]Since we split the total flow of workers within each pair into four occupation categories, the numerator of the dependent variable in equation (6) is smaller than in the baseline specification, hence both average flows and changes in flows are smaller.

[30]The idea that lack of skilled workers is a major hurdle for firm growth is supported not only by the literature emphasizing the 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-collar workers as much as STEM-skilled 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).

hit by an industry shock, a group is best served by a combination of industry diversification and geographical focus. Diversification across industries creates scope to reallocate workers from low to high marginal-revenue-productivity-of-labor units, whereas geographical proximity facilitates worker transfers.

Our findings are consistent with the role of business network in ironing out information frictions and boosting firm performance (see Cai and Szeidl (2018)). This raises 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 larger ability to adapt to changing business conditions with respect to stand-alone firms: thanks to the ILM, groups can overcome human capital bottlenecks that 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.[31]

An important question we intend to analyze in future research is whether group ILMs can facilitate the allocation of labor to more productive uses in the economy by reducing labor distortions. Using a general equilibrium framework where firing and hiring costs affect both business groups and stand-alone firms, a set up à la Hsieh and Klenow (2009) as revisited by Sraer and Thesmar (2018) will allow us to quantify the impact of groups' ILMs on misallocation.

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. 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.

However, taking the structure of complex organizations as given is far from fully satisfactory, and we also aim at understanding how such entities come to life, the constraints that arise to locate them in space, and why they take different forms. In particular, why are some units added to 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, in future research we plan to investigate how shocks lead to the addition of new firms within groups versus new establishments in multi-establishment firms.

[31] 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)).

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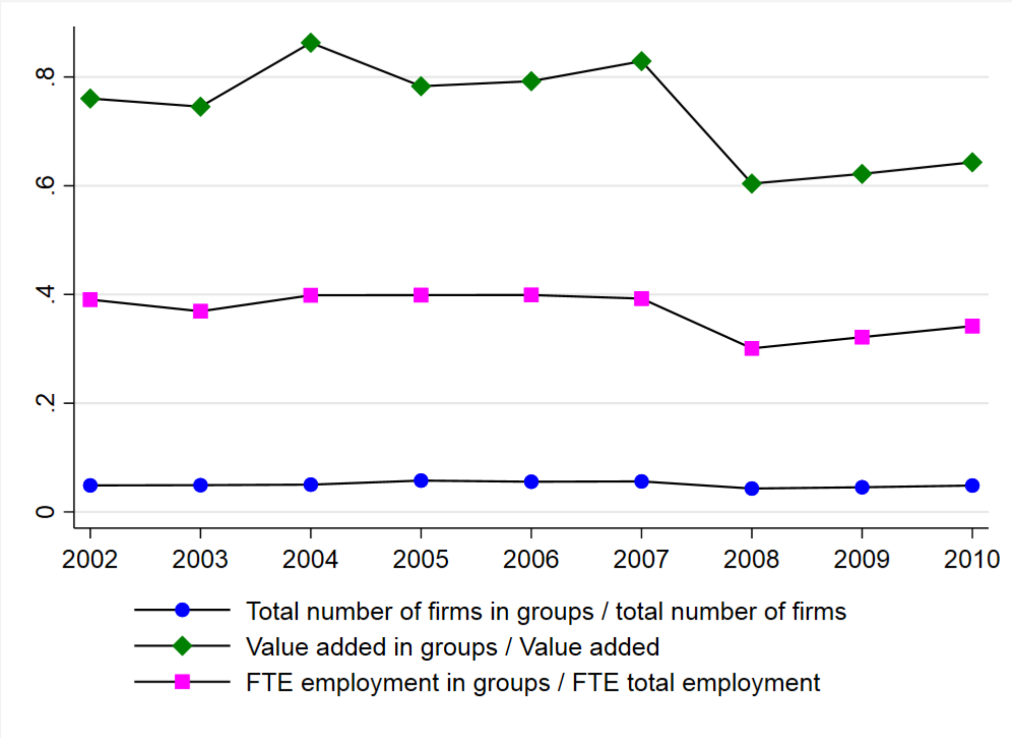
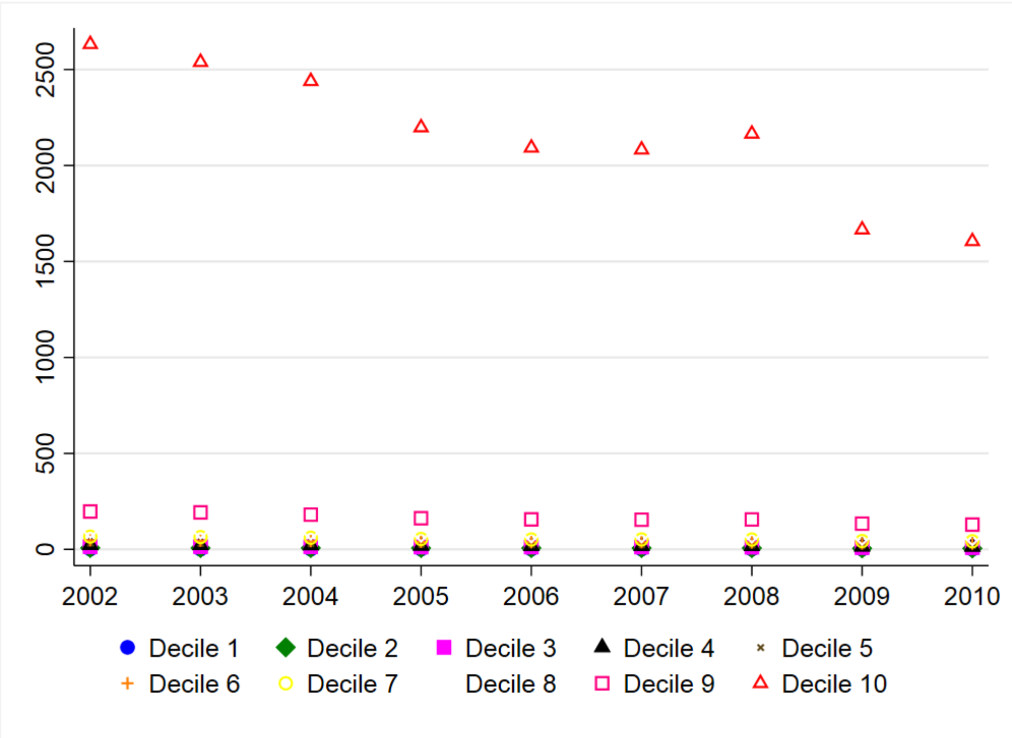
Figure 2: Business Groups in France



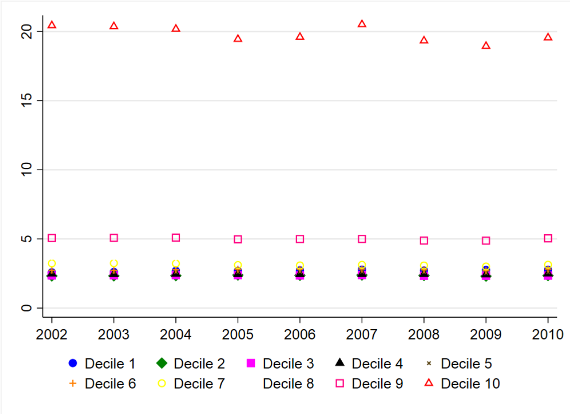
(a) Importance of group-affiliated firms in the French economy



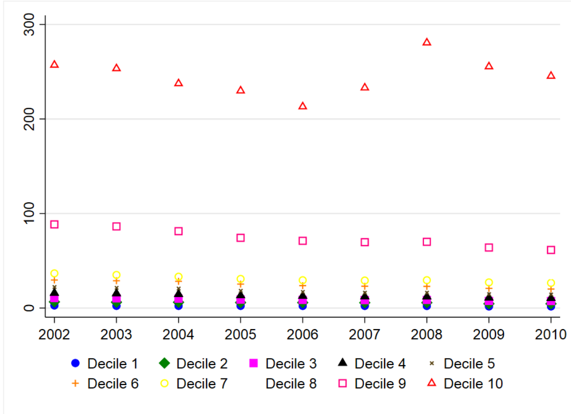
(b) Distribution of group size

Note: In panel (b), in each year French groups are ranked in ten deciles, based on size. Group size is measured as the group total number of (full-time equivalent) employees. For each year, the figure shows the average size of groups belonging to each decile.

Figure 3: Characteristics of the population of groups by decile of group size

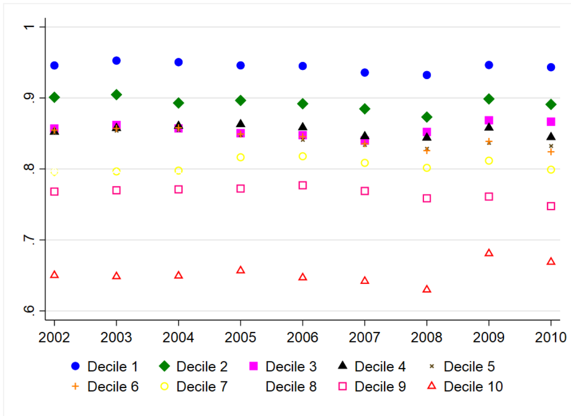


(a) Number of affiliates

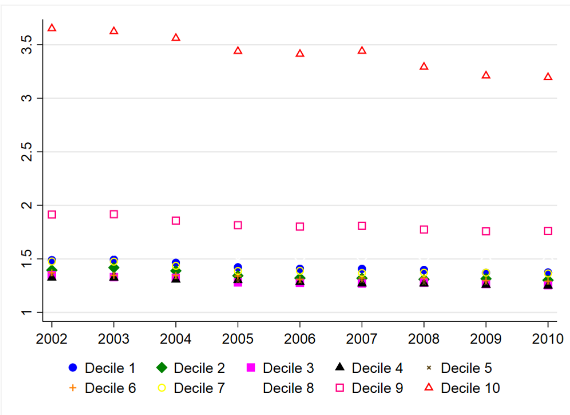


(b) Average size of affiliates

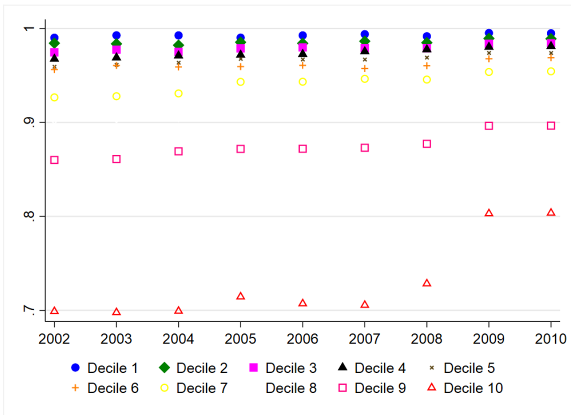
(c) Number of 4-digit industries



(d) Group concentration across 4-digit industries



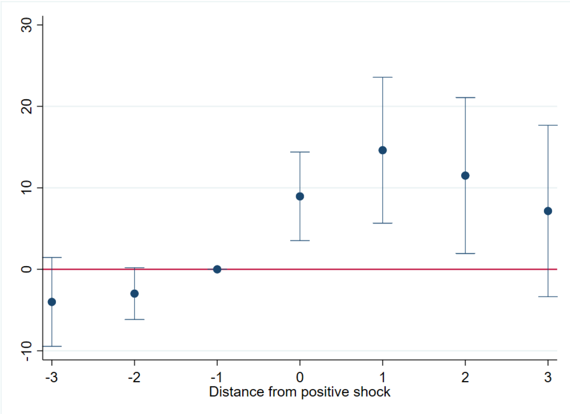
(e) Number of regions



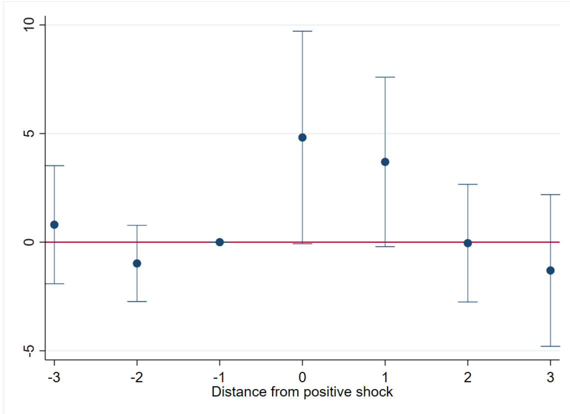
(f) Group concentration across regions

Note: In each year French groups are ranked in ten deciles, based on size. Group size is measured as the group total number of (full-time equivalent) employees. Each panel shows, for each year, the average value of a given group characteristic by decile of group size. Affiliates' size, in panel (b), is measured as the total number of (full-time equivalent) employees. Four-digit industries, in panel (c), are obtained from the INSEE classification NAF rev. 1, 2003. Group concentration across 4-digit industries/regions is measured as the group-level HHI, i.e. an HHI based on group employment shares in the different four-digit industries (panel (d)) and regions (panel (f)).

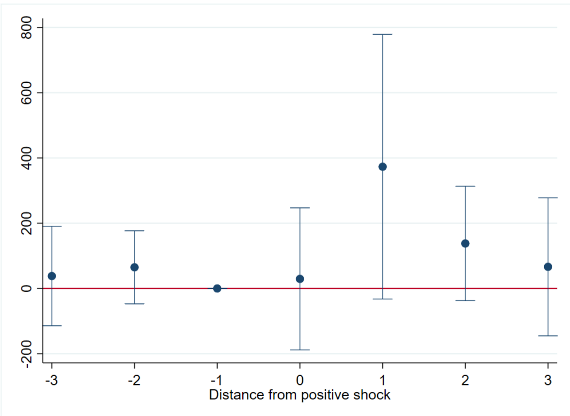
Figure 4: Impact of competitors' closures on shocked firms' outcomes



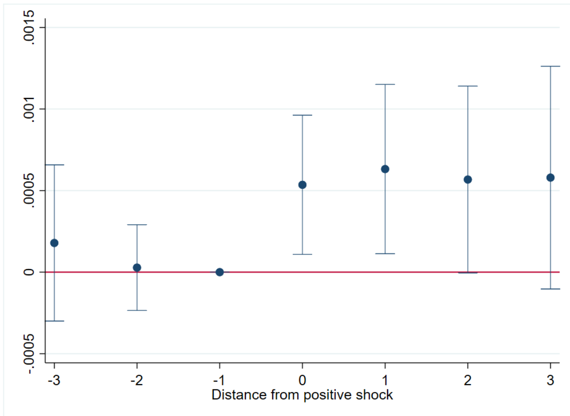
(a) Employment



(b) Hiring



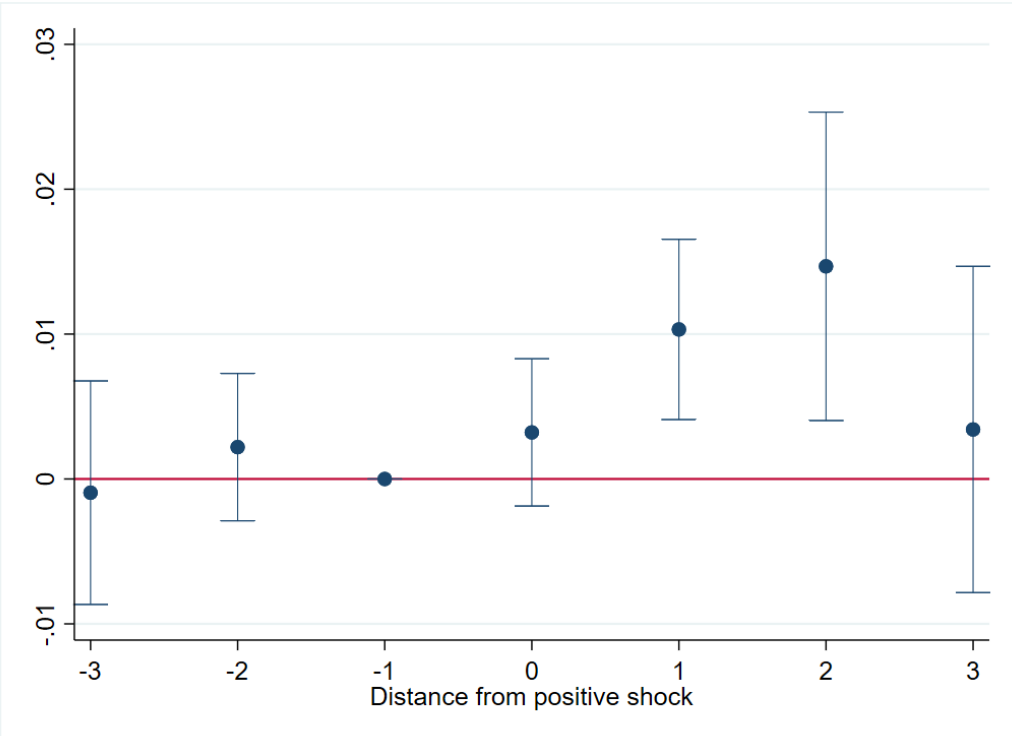
(c) Investment



(d) Market shares

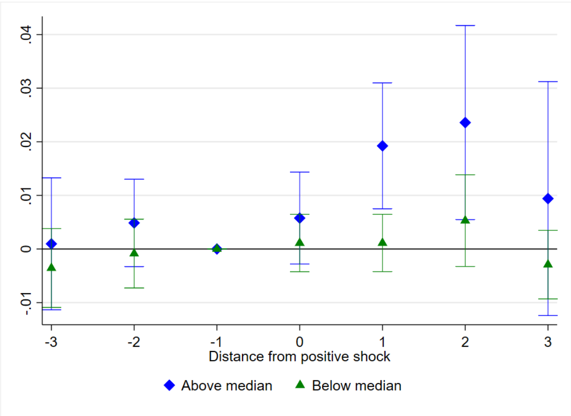
Note: In each panel, we plot the coefficients $\widehat{\alpha}_\tau - \widehat{\alpha}_{-1}$ estimated from equation (3). The plotted coefficients measure the change in each of the firm-level outcomes from event date -1 to event dates $\tau \in [-3, +3]$ (relative to the counterfactual flows). Event date 0 is the year of the 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 clustered at the industry and group level. *Employment* measures the total number of (full-time equivalent) employees of (shocked) firm j. *Hiring* measures the change in employment (of shocked firm j). *Investment* equals CapEx in 1000 EUR. *Market share* is the ratio of firm j's sales over total sales in its four-digit shocked industry s. Table A10 in the Appendix reports the estimated coefficients, s.e., and sample size.

Figure 5: Impact of competitors' closures on share of internal hires

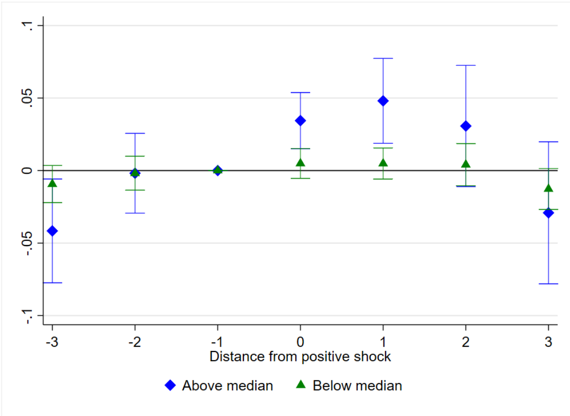


Note: The figure plots the coefficients $\widehat{\alpha}_\tau - \widehat{\alpha}_{-1}$ estimated from equation (3). The plotted coefficients measure the change in the share of internal hires from event date -1 to event dates $\tau \in [-3, +3]$ (relative to the counterfactual flows). Event date 0 is the year of the 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 clustered at the industry and group level. *Share of internal hires* is the ratio of new hires originating from same-group firms over total hiring of firm j. Table A10 in the Appendix reports the estimated coefficients, s.e., and sample size.

Figure 6: Share of internal hires and Number of active internal partners, by *ILM Access*



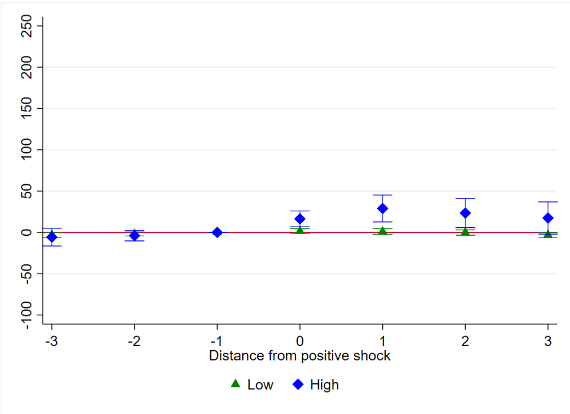
(a) Share of internal hires



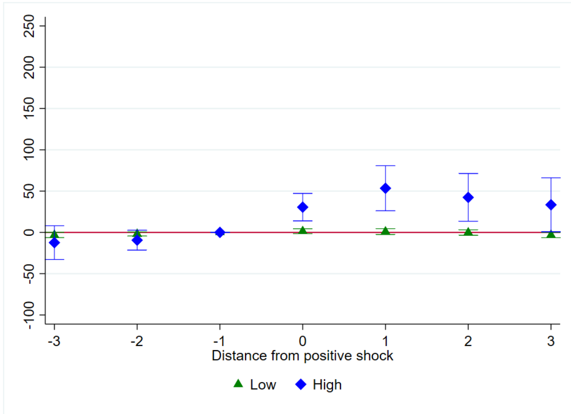
(b) NAIPs

Note: The figure shows the effect of a large competitor closure on shocked BG firms' *Share of internal hires* and *number of active internal labor market partners* (NAIPs), depending on the level of *ILM Access*, estimating equation (4). Active internal labor market partners are the internal partners from which the shocked BG firm j actually hires workers. *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 j; (iii) in a different 4-digit industry than j. The median value of *ILM Acces* is equal to 1 worker. 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 the outcome from event date -1 to event dates $\tau \in [-3, +3]$ (relative to the counterfactual) for firms with *ILM Access* above the median. The green triangles represent the change in the outcome for firms with below median *ILM Access*. Panel (a) shows that the change in Share of internal hires in above-median *ILM Access* firms is significantly higher than in below-median *ILM Access* firms: the difference is significant at 1% at $\tau = 1$ ($p = 0.0086$), and at 5% at $\tau = 2$ ($p = 0.0572$). Panel (b) shows that the change in NAIPs in above-median *ILM Access* firms is significantly higher than in below-median *ILM access* firms: the difference is significant at 5% at $\tau = 0$ ($p = 0.011$) and at 1% at $\tau = 1$ ($p = 0.008$). The error bars show the 95% confidence intervals calculated using standard errors that are clustered at the industry and group level. Table A12 in the Appendix reports the estimated coefficients, s.e., sample size.

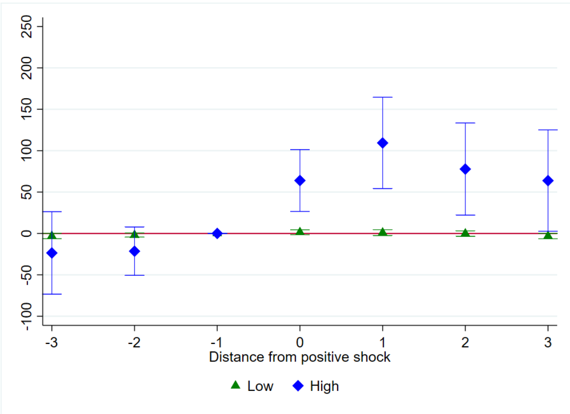
Figure 7: Impact of competitors' closures on BG firms' employment, by *ILM Access*



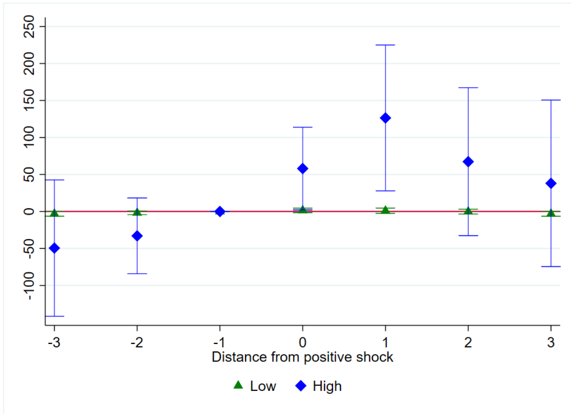
(a) ILM Access above median vs. below median



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



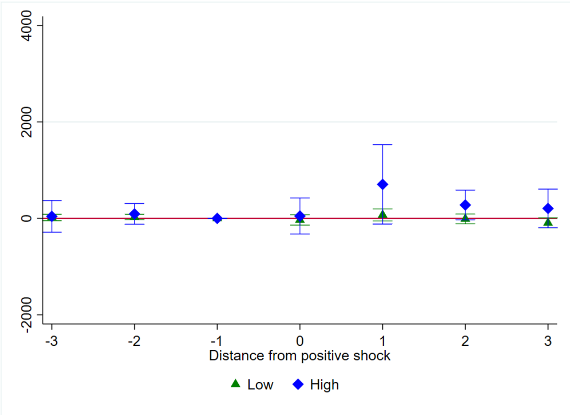
(c) ILM Access in top decile vs. below median



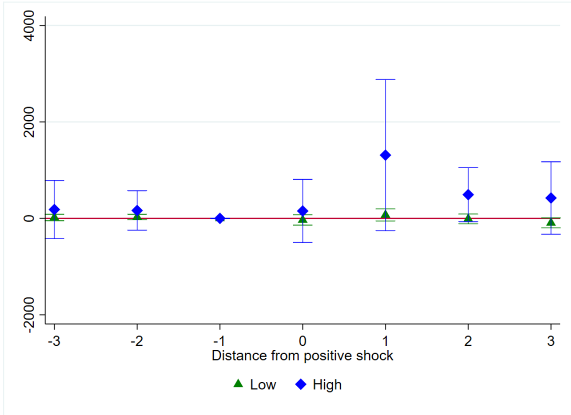
(d) ILM Access in top 5 percent vs. below median

Note: The figure shows the effect of a large competitor closure on shocked BG firms' employment, depending on the level of *ILM Access* (estimated using equation (4)). *ILM Access* is the sum of employment (measured at $\tau = -1$) of all group units that are (i) affiliated with 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 employment from event date -1 to event dates $\tau \in [-3, +3]$ (relative to the counterfactual) 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 employment 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. Table A13 in the Appendix reports the estimated coefficients, s.e., sample size.

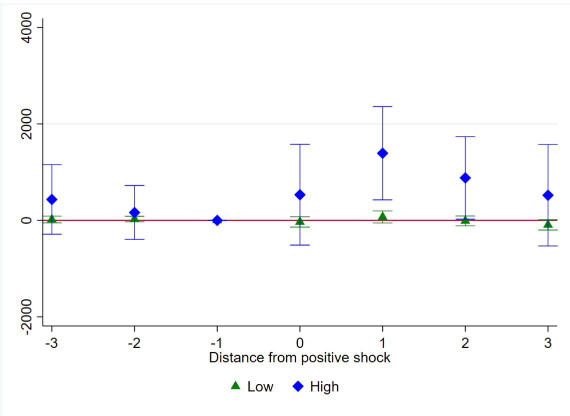
Figure 8: Impact of competitors' closures on BG firms' investment, by *ILM Access*



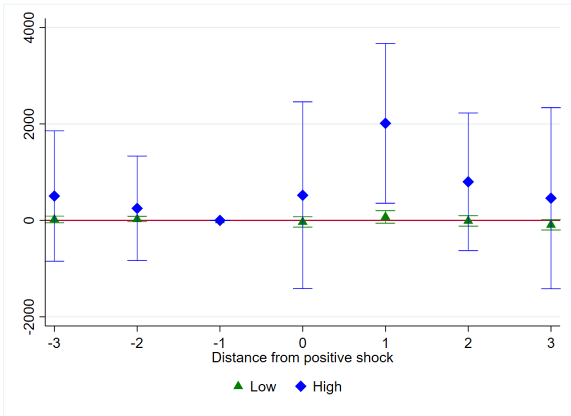
(a) ILM Access above median vs. below median



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



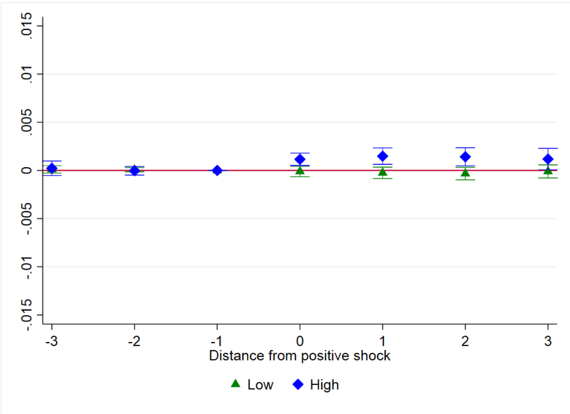
(c) ILM Access in top decile vs. below median



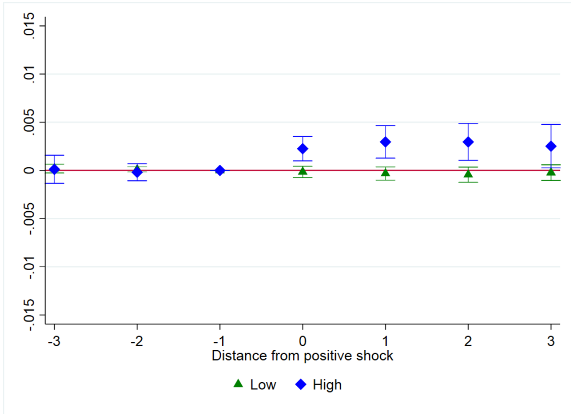
(d) ILM Access in top 5 percent vs. below median

Note: The figure shows the effect of a large competitor closure on shocked BG firms' investment (CapEx), depending on the level of *ILM Access* (estimated using 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 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 investment from event date -1 to event dates $\tau \in [-3, +3]$ (relative to the counterfactual) 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 investment for firms with below median *ILM Access*. Panel (c) shows that investment in high ILM access firms is significantly higher than in low ILM access firms: the difference is significant at 1% at $\tau = 1$ ($p = 0.0067$) and at 5% at $\tau = 2$ ($p = 0.035$). Panel (d) shows that investment in high ILM access firms is significantly higher than in low ILM access firms: the difference is significant at 5% at $\tau = 1$ ($p = 0.0209$). 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. Table A14 in the Appendix reports the estimated coefficients, s.e., sample size.

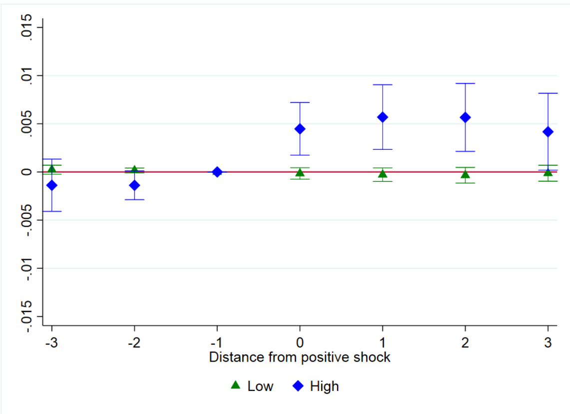
Figure 9: Impact of competitors' closures on BG firms' market shares, by *ILM Access*



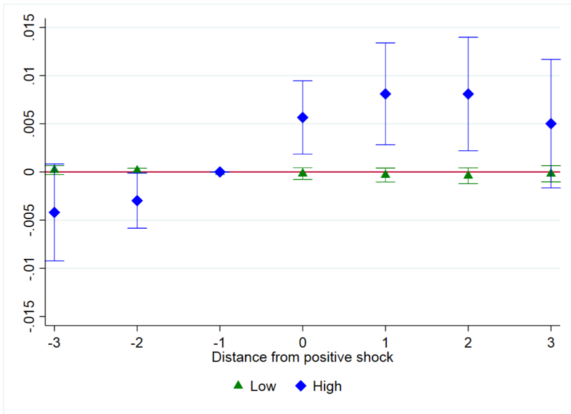
(a) ILM Access above median vs. below median



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



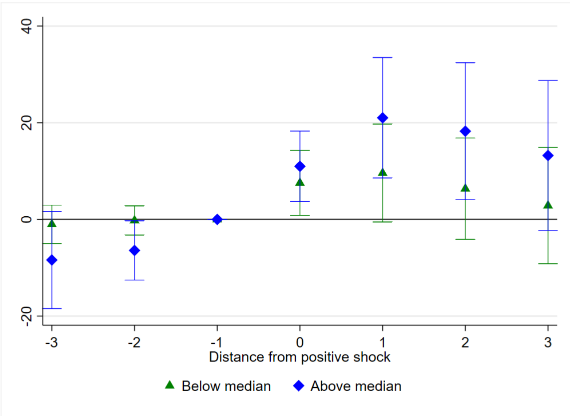
(c) ILM Access in top decile vs. below median



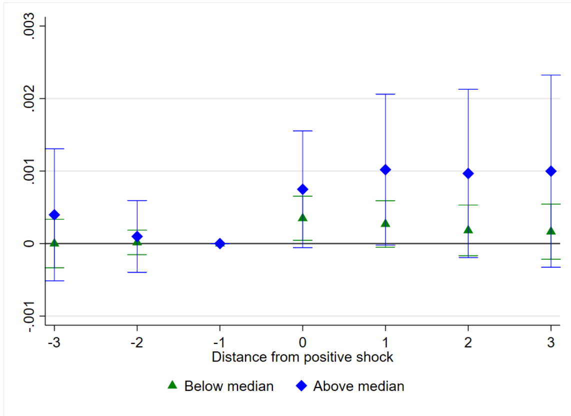
(d) ILM Access in top 5 percent vs. below median

Note: The figure shows the effect of a large competitor closure on shocked BG firms' market share, depending on the level of *ILM Access* (estimated using 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 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) 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. Table A15 in the Appendix reports the estimated coefficients, s.e., sample size.

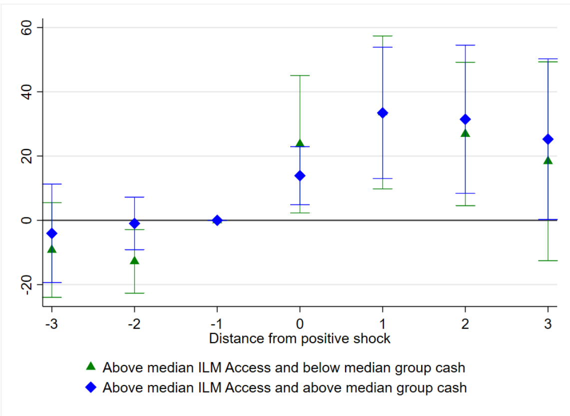
Figure 10: Impact of competitors' closures on BG firms' Employment and Market Share, by group industry diversification and group cash



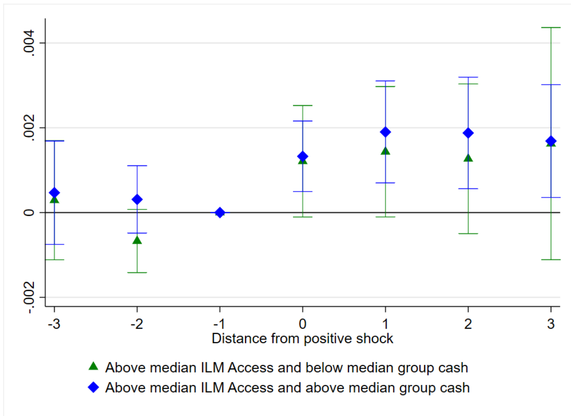
(a) Employment, by group Diversification



(b) Market Share, by group Diversification



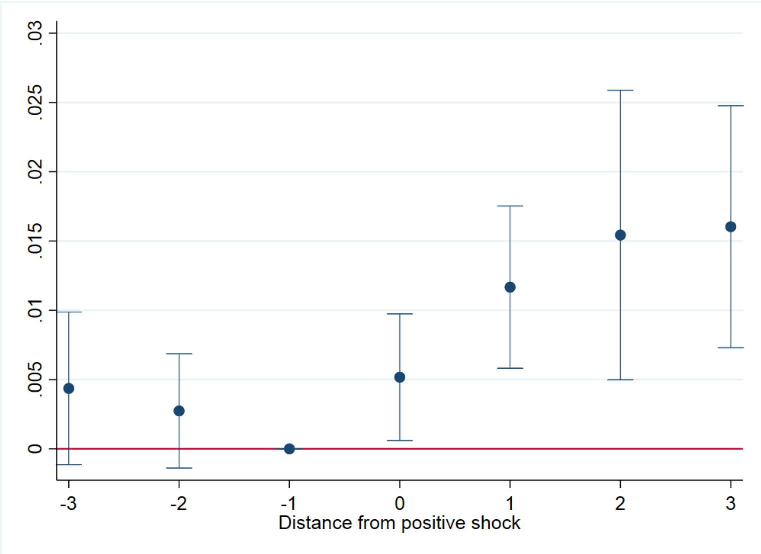
(c) Employment (high-ILM access firms), by group Cash



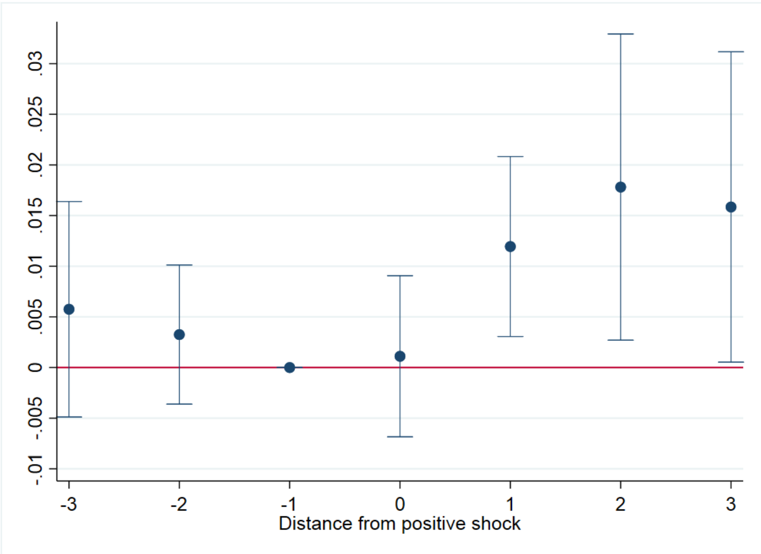
(d) Market Share (high-ILM access firms), by group Cash

Note: Panels (a) and (b) show the effect of a large competitor closure on shocked BG firms' Employment and Market Share, depending on the group's industry diversification. We measure (pre-shock) group industry diversification as the opposite of the group-level HHI, i.e. an HHI based on the employment shares in the different four-digit industries in which group affiliates operate at $\tau = -1$. Panels (c) and (d) show the effect of a large competitor closure on shocked BG firms' Employment and Market Share (for firms with ILM Access above median), depending on group cash. Group cash equals total cash over total assets of all subsidiaries affiliated with shocked BG firm 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 diamond (green triangles) plot the change in employment/market share from event date -1 to event dates $\tau \in [-3, +3]$ (relative to the counterfactual) for firms affiliated with groups with a diversification index/cash above (below) median. 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. Tables A16 and A17 in the Appendix report the estimated coefficients, s.e., sample size.

Figure 11: Impact of competitors' closures on bilateral worker flows from ILM partners



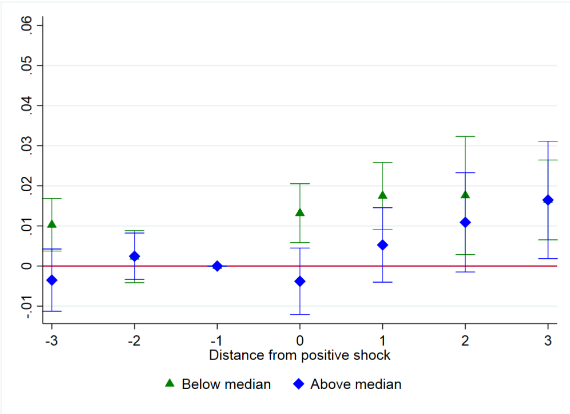
(a) Impact of competitors' closures on bilateral worker flows from ILM partners



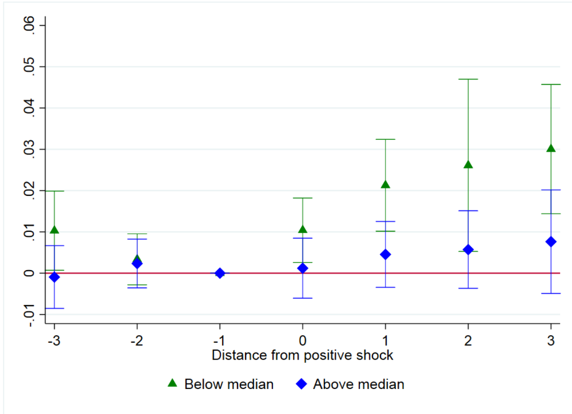
(b) Impact of competitors' closures on bilateral worker flows from ILM partners operating in same local labor market

Note: Panel (a) plots the coefficients $\widehat{\alpha}_{\tau}^{Int} - \widehat{\alpha}_{-1}^{Int}$ estimated from equation (5). Panel (b) plots the coefficients estimated in a specification in which flows occur within pairs where the firm of origin operates in the same local labor market as firm j. The coefficients measure the change in Internal 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 clustered at the industry and group level. 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 A20 in the Appendix reports the estimated coefficients, s.e., and sample size for panel (a) and Table A21, columns 1-2, for panel (b). Both Tables also report the estimated coefficients $\widehat{\alpha}_{\tau}^{Ext} - \widehat{\alpha}_{-1}^{Ext}$ regarding external flows.

Figure 12: Impact of competitors' closures on ILM flows, by firm of origin characteristics



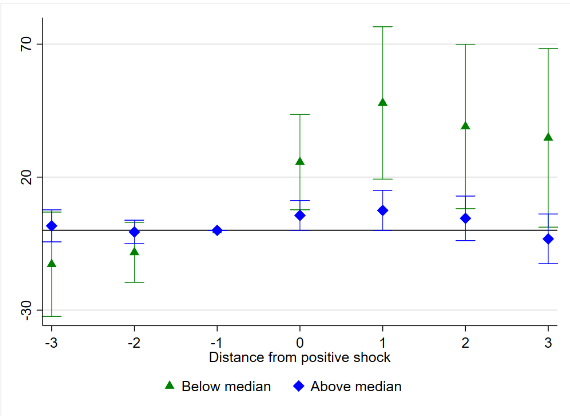
(a) Flows from firms with high vs low pre-event Value Added Per Worker



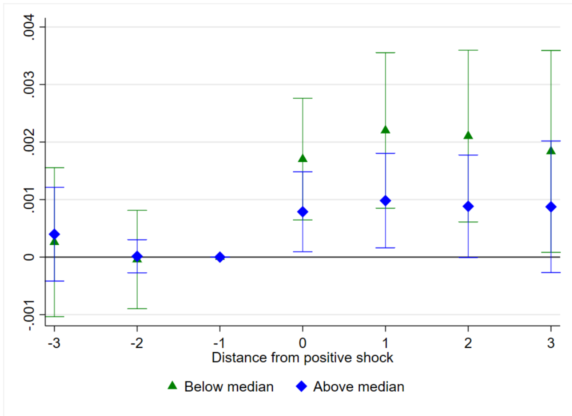
(b) Flows from firms with high vs low pre-event Capex

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 (computed in the overall sample of firms of origin affiliated with shocked BG firms). 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 (in the overall sample of firms of origin affiliated with shocked BG firms). 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 A22 in the Appendix reports the estimated coefficients, s.e., sample size.

Figure 13: Impact of competitors' closures on employment and market shares, by Value Added per Worker of the least productive group-affiliate within the local labor market



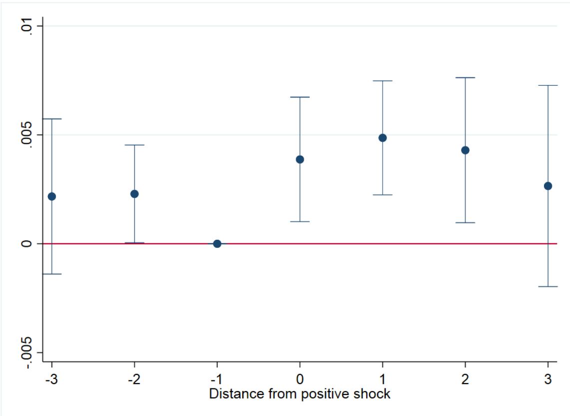
(a) Employment



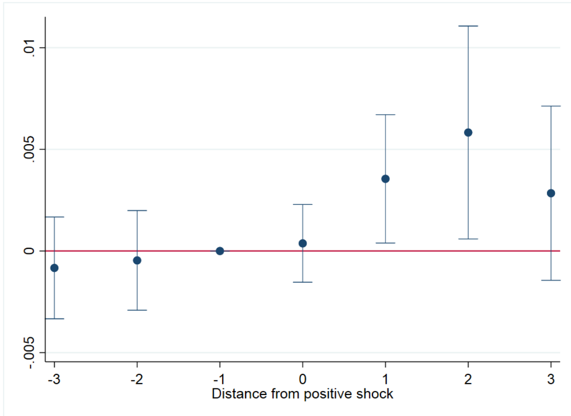
(b) Market shares

Note: The figure shows the effect of a large competitor closure on shocked BG firms' employment (panel (a)) and market shares (panel (b)) depending on the (pre-shock) VA per Worker of the least productive affiliate of the rest of the group. For each shocked BG firm, we focus on the subset of group affiliates located within the same local labor market as the shocked firm and active in non-shocked sectors, and we identify the affiliate with the lowest VA per Worker. We then separate shocked firms depending on the level of VA per Worker of the least productive affiliate, i.e. whether they are above or below the median of the distribution of VA per Worker of the least productive affiliate. The reason for focusing on rest-of-the-group affiliates located in the same local labor market as the shocked firm is that reallocations beyond the so called *Zone d'Emploi* are likely to encounter substantial hurdles in France, as discussed in Section 5.2. Hence, affiliates active in non-shocked sectors but outside the local labor market are unlikely to contribute to within-group efficiency enhancing reallocations. Panel (a) shows that employment in shocked firms whose least productive affiliate is below the median is significantly higher than in shocked firms above the median: the difference is significant at 5% at $\tau = 0$ ($p = 0.033$), at 1% at $\tau = 1$ ($p = 0.0057$), $\tau = 2$ ($p = 0.0029$) and $\tau = 3$ ($p = 0.0025$). Panel (b) shows that market shares in shocked firms below the median are higher than in shocked firms above the median: the difference is marginally significant at 10% at $\tau = 0$ ($p = 0.11$) and $\tau = 1$ ($p = 0.09$). 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 A23 in the Appendix reports the estimated coefficients, standard errors and sample size.

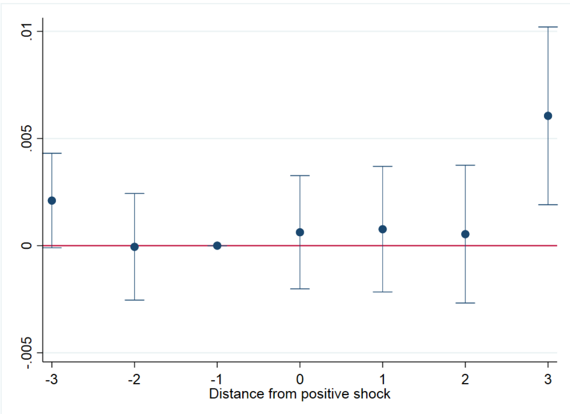
Figure 14: Impact of competitors' closures on ILM flows, by occupation



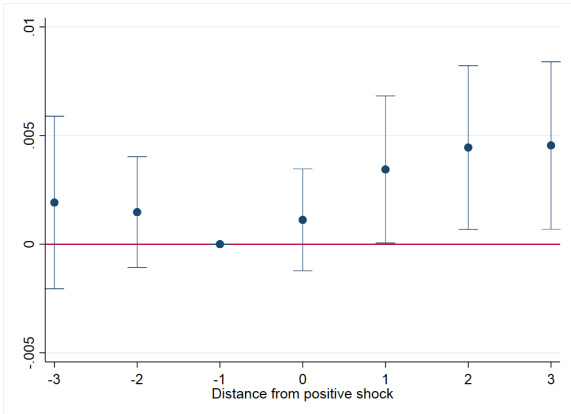
(a) Blue Collars



(b) Clerical Workers



(c) Intermediate Professions



(d) Managers/High-skill

Note: The figure plots the coefficients $\widehat{\alpha}_{\tau}^{Int} - \widehat{\alpha}_{-1}^{Int}$ (blue dots) estimated from equation 6. We consider 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 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×occupation fixed effects and year dummies in our specification. Table A24 in the Appendix reports the estimated coefficients, s.e., sample size. The Tables also report the estimated coefficients $\widehat{\alpha}_{\tau}^{Ext} - \widehat{\alpha}_{-1}^{Ext}$ regarding external flows.

Table 1. Excess probabilities of within-group firm-to-firm transitions

	mean	sd	p10	p25	p50	p75	p90	N
Unconditional excess probabilities	0.052	0.156	-0.000	-0.000	-0.000	0.010	0.143	318,452
Controlling for propensity to hire workers moving:								
Between any local labor markets	0.052	0.157	-0.000	-0.000	-0.000	0.010	0.140	318,452
Within same local labor market	0.063	0.188	-0.000	-0.000	-0.000	0.002	0.200	306,452
Between any occupations	0.096	0.240	-0.000	-0.000	0.000	0.014	0.334	318,447
Within same occupation	0.072	0.211	-0.000	-0.000	0.000	0.001	0.236	298,987
Between any occupations × local labor market	0.101	0.249	-0.000	-0.000	0.000	0.018	0.400	318,435
Within same occupation×local labor market	0.081	0.234	-0.000	-0.000	0.000	0.000	0.263	264,644

Note: Row 1 displays descriptive statistics on the unconditional excess probabilities $\widehat{\gamma}_{j,t}$ estimated from equation (1) when the set c is the set of all job movers in the French economy. In row 2 we define c as the subset of job movers transiting between local labor markets l and local labor market m. The estimated $\widehat{\gamma}_{c,j,t}$ are aggregated at the firm-level taking simple averages to obtain excess probabilities $\widehat{\gamma}_{j,t}$. In row 3 the set c includes job movers transiting within the same local labor market ($l = m$). In row 4 we define c as the subset of job movers transiting between occupation o and occupation z. In row 5 we define c as the subset of job movers transiting between the same occupations ($o = z$). In row 6 we define c as the subset of job movers transiting between two specific occupations and local labor markets. In row 7 we define the set c as the subset of job movers transiting between the same occupations and the same local labor markets.

Table 2. ILM activity (excess probabilities) 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 (obtained averaging at the firm level the $\widehat{\gamma}_{c,j,t}$ estimated controlling for firm ×occupation-pair fixed effects). *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. Group *Diversification (macrosectors/4-digit sectors/Paris/Regions)* is computed as the opposite of the sum of the squares of all 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 to account for unobserved heterogeneity at the firm × group level (since firms may change the group they are affiliated with, firm effects do not capture the firm × group match-specific unobserved heterogeneity), 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. The Table 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 3. Quantifying the value of ILM: value created by relaxing the constraint

	Below median HHI	Above median HHI
Group HHI across industries	0.46	0.89
	(0.13)	(0.10)
	$N = 501$	$N = 501$
λ (in thousands of euros)		
- labor share=2/3	165.31	39.51
	(1027.87)	(178.68)
- labor share=1/2	123.98	29.63
	(770.90)	(134)
	$N = 501$	$N = 501$
Group EBITDA	59,539.7	32,194.64
	(441,355.9)	(474,730.6)
	$N = 501$	$N = 500$
Internal hiring pre-shock	1.27	0.350
	(14.41)	(1.99)
	$N = 362$	$N = 358$
Number of affiliates outside shocked industries (pre-shock)	17.27	3.25
	(57.97)	(8.88)
	$N = 501$	$N = 501$
Number of non-shocked industries (pre-shock)	6.02	1.95
	(9.36)	(3.33)
	$N = 501$	$N = 495$
Employment of shocked firm (pre-shock)	100.16	102.76
	(238.13)	(281.52)
	$N = 501$	$N = 501$
Share of group employment in non- shocked industries located in a different department (pre-shock)	0.91	0.74
	(0.26)	(0.43)
	$N = 485$	$N = 371$
Share of group employment in non-shocked industries that located in a different region (pre-shock)	0.70	0.56
	(0.41)	(0.48)
	$N = 485$	$N = 371$

Notes: The table reports the calculated value of the wedge λ measuring within-group labor misallocation after the shock. Out of the 3,466 shocked BG firms with below-median *ILM Access*, we focus on those that have at least one affiliate in a non-shocked sector. For shocked BG firms whose group only operates in the shocked industry at $\tau = -1$, this exercise is not feasible: given the sectoral nature of the shock in our paper, the ability to use the ILM is intrinsically linked to the group being active across the shocked and non-shocked sectors. The table also reports a series of pre-shock firm/group characteristics, for firms affiliated with groups with high/low industry diversification (below/above median HHI). The number of observations drops to 1007 due to 594 missing values in λ and to 1002 due to missing values in the HHI. It can further vary due to missing values in the remaining variables.

A Appendix

A.1 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.2 Descriptive evidence on business groups' propensity to hire internally

A.2.1 Methodology

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

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:

$$R^{BG}_{c,j,t} \equiv \frac{\sum_{i \in c,k} E_{i,c,k,j,t} BG_{i,k,j,t}}{\sum_{i \in c,k} BG_{i,k,j,t}} = \beta_{c,j,t} + \gamma_{c,j,t} + \widetilde{u}^{BG}_{c,j,t} \tag{7}$$

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:

$$R^{-BG}_{c,j,t} \equiv \frac{\sum_{i \in c,k} E_{i,c,k,j,t}(1 - BG_{i,k,j,t})}{\sum_{i \in c,k}(1 - BG_{i,k,j,t})} = \beta_{c,j,t} + \widetilde{u}^{-BG}_{c,j,t} \tag{8}$$

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 (7) and (8) 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 $\beta_{c,j,t}$:

$$G_{cj,t} \equiv R^{BG}_{c,j,t} - R^{-BG}_{c,j,t} = \gamma_{c,j,t} + u^{G}_{i,j,t}. \tag{9}$$

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 set c, we identify the firm-to-firm movers in set c (e.g. workers moving between two given occupations o and z) between year $t-1$ and year t. Then, we associate each set 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 (7) and (8).[32] For each pair $\{c, j\}$, we then compute the number of firm-to-firm

[32] 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

movers in set 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 (7) and (8), and ultimately to estimate our parameter of interest $\gamma_{c,j,t}$ for each set-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 set $c \times$ 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 sets.[33] 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 A3.

Equivalence result: *The coefficient $\widehat{\gamma}_{c,j,t}$ estimated in equation* (9) *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:

$$\begin{aligned}
\gamma^{OLS}_{c,j} &= \frac{Cov(E_{i,c,j}, BG_{i,j})}{Var(BG_{i,j})} = \frac{\sum_{i=1}^{N}(E_{i,c,j} - \overline{E}_{c,j})(BG_{i,j} - \overline{BG}_j)/N}{\sum_{i=1}^{N}(BG_{i,j} - \overline{BG}_j)^2/N} \\
&= \frac{\sum_{i=1}^{N} E_{i,c,j}BG_{i,j}/N - \overline{E}_{c,j}\overline{BG}_j}{\sum_{i=1}^{N} BG^2_{i,j}/N - \overline{BG}^2_j} = \frac{\sum_{i=1}^{N} E_{i,c,j}BG_{i,j}/N - \overline{E}_{c,j}\overline{BG}_j}{\overline{BG}_j - \overline{BG}^2_j} \qquad (10)
\end{aligned}$$

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:

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

Hence,

$$\begin{aligned}
(\overline{BG}_j - \overline{BG}^2_j)(\gamma^{OLS}_{c,j} + \beta^{OLS}_{c,j}) &= \sum_{i=1}^{N} E_{i,c,j}BG_{i,j}/N - \overline{BG}^2_j(\beta^{OLS}_{c,j} + \gamma^{OLS}_{c,j}) \qquad (11) \\
\gamma^{OLS}_{c,j} + \beta^{OLS}_{c,j} &= \frac{\sum_{i=1}^{N} E_{i,c,j}BG_{i,j}/N}{\overline{BG}_j} = \frac{\sum_{i=1}^{N} E_{i,c,j}BG_{i,j}}{\sum_{i=1}^{N} BG_{i,j}} \qquad (12)
\end{aligned}$$

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.

[33] 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.

as in equation (7). Next, substituting (10) 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 (8). □

A.2.2 Descriptive statistics: estimated excess probabilities by year

Table A2. 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	36,302
2004	0.053	0.158	-0.000	-0.000	-0.000	0.011	0.143	35,594
2005	0.052	0.156	-0.000	-0.000	-0.000	0.011	0.143	37,682
2006	0.053	0.156	-0.000	-0.000	-0.000	0.011	0.150	40,294
2007	0.049	0.149	-0.000	-0.000	-0.000	0.008	0.143	42,864
2008	0.047	0.146	-0.000	-0.000	-0.000	0.007	0.125	45,672
2009	0.055	0.160	-0.000	-0.000	-0.000	0.012	0.164	39,293
2010	0.057	0.169	-0.000	-0.000	-0.000	0.010	0.167	40,751

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 A3. Mean excess probability of within-group firm-to-firm transitions by year

			Percentiles								Percentiles					
Year	Mean	St.Dev.	10	25	50	75	90	N	Mean	St.Dev.	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	36,302	0.060	0.181	-0.000	-0.000	-0.000	0.001	0.167	34,945
2004	0.053	0.159	-0.000	-0.000	-0.000	0.010	0.143	35,594	0.064	0.190	-0.000	-0.000	-0.000	0.001	0.200	34,152
2005	0.052	0.158	-0.000	-0.000	-0.000	0.011	0.143	37,682	0.065	0.192	-0.000	-0.000	-0.000	0.002	0.200	36,257
2006	0.053	0.158	-0.000	-0.000	-0.000	0.011	0.146	40,294	0.066	0.192	-0.000	-0.000	-0.000	0.002	0.200	38,552
2007	0.048	0.150	-0.000	-0.000	-0.000	0.008	0.125	42,864	0.060	0.181	-0.000	-0.000	-0.000	0.001	0.171	41,233
2008	0.047	0.147	-0.000	-0.000	-0.000	0.007	0.125	45,672	0.058	0.178	-0.000	-0.000	-0.000	0.001	0.167	44,060
2009	0.055	0.164	-0.000	-0.000	-0.000	0.011	0.162	39,293	0.066	0.194	-0.000	-0.000	-0.000	0.002	0.200	37,774
2010	0.056	0.171	-0.000	-0.000	-0.000	0.009	0.167	40,751	0.065	0.193	-0.000	-0.000	-0.000	0.002	0.200	39,479
	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	36,302	0.068	0.204	-0.000	-0.000	0.000	0.001	0.200	34,057
2004	0.097	0.241	-0.000	-0.000	0.000	0.017	0.370	35,594	0.072	0.211	-0.000	-0.000	0.000	0.001	0.250	33,244
2005	0.098	0.242	-0.000	-0.000	0.000	0.017	0.379	37,682	0.072	0.212	-0.000	-0.000	0.000	0.001	0.243	35,186
2006	0.098	0.242	-0.000	-0.000	0.000	0.018	0.375	40,294	0.073	0.213	-0.000	-0.000	0.000	0.001	0.250	37,768
2007	0.091	0.233	-0.000	-0.000	0.000	0.011	0.333	42,864	0.067	0.203	-0.000	-0.000	0.000	0.000	0.200	40,242
2008	0.089	0.230	-0.000	-0.000	0.000	0.010	0.333	45,672	0.068	0.205	-0.000	-0.000	0.000	0.000	0.200	43,208
2009	0.101	0.247	-0.000	-0.000	0.000	0.018	0.417	39,288	0.078	0.221	-0.000	-0.000	0.000	0.001	0.250	37,030
2010	0.100	0.248	-0.000	-0.000	0.000	0.013	0.400	40,751	0.075	0.219	-0.000	-0.000	0.000	0.001	0.250	38,252
	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	36,302	0.079	0.230	-0.000	-0.000	0.000	0.000	0.250	29,914
2004	0.102	0.250	-0.000	-0.000	0.000	0.020	0.417	35,594	0.082	0.236	-0.000	-0.000	0.000	0.000	0.278	29,175
2005	0.104	0.251	-0.000	-0.000	0.000	0.021	0.431	37,682	0.082	0.236	-0.000	-0.000	0.000	0.000	0.274	31,034
2006	0.104	0.251	-0.000	-0.000	0.000	0.022	0.417	40,293	0.084	0.238	-0.000	-0.000	0.000	0.000	0.333	32,976
2007	0.097	0.243	-0.000	-0.000	0.000	0.014	0.333	42,864	0.078	0.229	-0.000	-0.000	0.000	0.000	0.250	35,695
2008	0.094	0.240	-0.000	-0.000	0.000	0.012	0.333	45,672	0.078	0.228	-0.000	-0.000	0.000	0.000	0.250	38,282
2009	0.107	0.256	-0.000	-0.000	0.000	0.023	0.500	39,282	0.087	0.243	-0.000	-0.000	0.000	0.000	0.333	32,798
2010	0.104	0.255	-0.000	-0.000	0.000	0.017	0.441	40,746	0.080	0.232	-0.000	-0.000	0.000	0.000	0.250	34,770

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 $\times$ 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 $\times$ 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 $\times$ occupation pair $\times$ 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.

A.2.3 Descriptive statistics of the regression sample used in Table 2

Table A4. 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	217,640	289,689
(Log) Firm size	3.593	1.481	-5.298	12.291	289,689
Rest of the group size (empl.)	10,955	29,375.43	0.001	349,038	289,689
(Log) Rest of the group size	6.107	2.786	-6.908	12.763	289,689
Number of 4-digit industries	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 industries)	-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: Descriptive statistics for the regression sample of Table 2. *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 industries/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 section 2.2.

A.2.4 Descriptive statistics: Intra-group mobility for different occupational categories

We also 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, we rank the two-digit occupation categories provided in the DADS (Table A1, Appendix A.1) by the estimated excess probabilities $\widehat{\gamma}_{c,j,t}$. Results in Table A5 suggest that the propensity to hire internally varies significantly across occupations, and is most intense for high-skilled occupations and occupations involving technical skills. The same pattern emerges in Table A6 (column 1), where we relate the estimated $\widehat{\gamma}_{c,j,t}$ to occupational categories (organized in broader groups: managers, engineers, and professionals; intermediate professions; clerical support, services, and sales workers; blue-collars) controlling for firm- and group-level time-varying confounders, time dummies and firms×group fixed effects. Even when focusing on horizontal job moves, we observe a higher propensity to hire internally for high-skilled occupations (columns 2 and 3).

Table A5. 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 estimated excess probabilities. The third column in each panel reports, for a given occupation, the average of all $\widehat{\gamma}_{c,j,t}$ 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 A6. 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 other firms affiliated with firm j's group. *State Control* is a dummy variable taking the value 1 if the group head is state-owned. *Foreign Control* is a dummy variable taking the value 1 if the group head is foreign. We organize the occupational categories listed in Table A1 (Appendix A.1) into four groups: (i) managers, engineers, professionals; (*ii*) intermediate professions; (*iii*) clerical support, services, sales workers; (iv) blue-collars. *Same Occupation* is a dummy variable taking the value 1 if occupation of origin is equal to occupation of destination. We control for firm × group fixed effects, and include year dummies. One star denotes significance at 5% level; two stars at 1% level; three stars denote significance at 0.1% level. The Table 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).

A.3 ILM Model: Formal Results and Proofs

In this section we formally derive solutions to the model presented in section 3.

The headquarters choose $e_A \geq 0$, $e_B \geq 0$ and i so as to maximize the total value of the group, subject to the ILM constraint, hence the problem Lagrangian is:[34]

$$V = (p_A + \varepsilon)\theta_A f(L_{0A} + e_A + i) - w(L_{0A} + e_A + i) - He_A$$
$$+ p_B\theta_B f(L_{0B} + e_B - i) - w(L_{0B} + e_B - i) - He_B + \lambda[\mu L_{0B} + e_B - i]$$

Clearly, at the optimum workers are never reallocated from positively shocked unit A to unit B, i.e. $i^* \geq 0$. Also, unit B does not hire on the external labor market, i.e. $e_B^* = 0$.[35] Taking this into account, the Kuhn-Tucker conditions are:

$$\frac{\partial V}{\partial e_A} = \begin{cases} (p_A + \varepsilon)\theta_A f'(L_{0A} + e_A^* + i^*) = w + H & \text{if } e_A^* > 0 \\ (p_A + \varepsilon)\theta_A f'(L_{0A} + i^*) \leq w + H & \text{if } e_A^* = 0 \end{cases} \tag{13a}$$

$$\frac{\partial V}{\partial i} = (p_A + \varepsilon)\theta_A f'(L_{0A} + e_A^* + i^*) - p_B\theta_B f'(L_{0B} - i^*) - \lambda = 0 \tag{13b}$$

$$\frac{\partial V}{\partial \lambda} = \mu L_{0B} - i^* \geq 0 \tag{13c}$$

$$\lambda \geq 0 \qquad \lambda[\mu L_{0B} - i^*] = 0 \tag{13d}$$

where λ is the Lagrange multiplier associated to the ILM constraint.

Inspection of these conditions suggests that optimal labor adjustment in a group depends on the thickness of its ILM, i.e. the size of μL_{0B}, as well as the size of the shock ε, as shown in the following Proposition.

Proposition 1. ***Optimal labor adjustment in a business group***
When unit A is hit by a positive shock, the optimal adjustment policy in the group entails $i^* \geq 0$, $e_A^* \geq 0$ and $e_B^* = 0$. Two cases arise depending on the size of μ.

Case I: Thick ILM.
When $\mu \geq \overline{\mu}$ the constraint $i \leq \mu L_{0B}$ is slack; there exists a threshold level ε^{nb} such that:

$$e_A^* = 0,\ i^* > 0, \quad s.t.\ \ (p_A + \varepsilon)\theta_A f'(L_{0A} + i^*) = p_B\theta_B f'(L_{0B} - i^*) < w + H \qquad if \ \ \varepsilon \in [0, \varepsilon^{nb})$$
$$e_A^* > 0,\ i^* > 0, \quad s.t.\ \ (p_A + \varepsilon)\theta_A f'(L_{0A} + e_A^* + i^*) = p_B\theta_B f'(L_{0B} - i^*) = w + H \qquad if \ \ \varepsilon \geq \varepsilon^{nb}$$

Case II: Thin ILM.
When $\mu < \overline{\mu}$, the constraint binds unless the shock is sufficiently small. Namely, there exist two

[34]Without loss of generality, we assume $w - F \leq p_A\theta_A f'(L_{0A}) = p_B\theta_B f'(L_{0B}) \leq w + H$, where $F \geq 0$ are per unit firing costs. If one relaxes this assumption, similar qualitative results obtain by re-scaling the threshold levels of the shock in Proposition 1. Also, allowing the marginal productivity of labor to be larger than $w + H$ would entail an additional case where unit B optimally increases its workforce at the same time as A, hence both units adjust using the external labor market only

[35]In principle, the group could have unit B hire workers on the external market and redeploy them to the positively shocked unit. Due to the presence of a small cost of internal reallocations this is never optimal.

thresholds, ε_b and ε^b, with $\varepsilon^b > \varepsilon_b$, such that:

$$e_A^* = 0,\ i^* > 0, \qquad s.t.\ \ (p_A+\varepsilon)\theta_A f'(L_{0A}+i^*) = p_B\theta_B f'(L_{0B}-i^*) < w+H \qquad if \varepsilon \in [0,\varepsilon_b] \tag{14a}$$

$$e_A^* = 0,\ i^* = \mu L_{0B},\ \ s.t.\ \ (p_A+\varepsilon)\theta_A f'(L_{0A}+i^*) - p_B\theta_B f'(L_{0B}-i^*) = \lambda > 0 \qquad if \varepsilon \in [\varepsilon_b,\varepsilon^b] \tag{14b}$$

$$e_A^* > 0,\ i^* = \mu L_{0B},\ \ s.t.\ \ (p_A+\varepsilon)\theta_A f'(L_{0A}+e_A^*+i^*) = p_B\theta_B f'(L_{0B}-i^*) + \lambda = w+H \qquad if \varepsilon \geq \varepsilon^b \tag{14c}$$

Proof. Let us consider first the case in which $\mu = 1$ and all the workers employed by unit B can be redeployed to unit A. For any $\varepsilon > 0$, define as $\widehat{i}(\varepsilon)$ the ILM flow that equalizes the marginal revenue product of labor across the two units, absent external adjustments: $(p_A+\varepsilon)\theta_A f'(L_{0A}+\widehat{i}(\varepsilon)) = p_B\theta_B f'(L_{0B}-\widehat{i}(\varepsilon))$.

From concavity of the production functions, $p_A\theta_A f'_A(L_{0A}) = p_B\theta_B f'_B(L_{0B})$ and $\lim_{L_i\to 0} f'(L_i) \to \infty$ it follows that $\widehat{i}(\varepsilon) < L_{0B}$ exists, it is unique and strictly increasing in ε, and it is positive if (and only if) $\varepsilon > 0$. Moreover, $p_A\theta_A f'_A(L_{0A}) = p_B\theta_B f'_B(L_{0B}) < w+H$ and $\lim_{L_B\to 0} f'(L_B) \to \infty$ imply that there exists a threshold level of the shock $\varepsilon^{nb} > 0$, such that when $\varepsilon \leq \varepsilon^{nb}$, it is: $p_B\theta_B f'(L_{0B}-\widehat{i}(\varepsilon)) = (p_A+\varepsilon)\theta_A f'(L_0+\widehat{i}(\varepsilon)) \leq w+H$ with $\widehat{i}(\varepsilon) > 0$. At $\varepsilon = \varepsilon^{nb}$, the ILM reallocation that equalizes the marginal revenue product of labor across the two units also ensures these are equal to $w+H$.

Therefore, for any $\varepsilon \leq \varepsilon^{nb}$, the optimal internal reallocation is $i^*(\varepsilon) = \widehat{i}(\varepsilon) < L_{0B}$, and it is optimal not to hire from the external labor market (i.e. $e_A^* = 0$). Conversely, when $\varepsilon > \varepsilon^{nb}$, $\widehat{i}(\varepsilon) > \widehat{i}(\varepsilon^{nb})$ and the internal reallocation that equalizes the marginal revenue products without external adjustments would make such marginal revenue products larger than $w+H$. This implies that the Kuhn-Tucker conditions can only be satisfied if $e_A^* > 0$. Indeed, under the assumptions that hiring costs are linear and that internal reallocations entail an infinitesimal cost, the unique solution is such that the optimal internal reallocation $\bar{i}$ does not vary with ε and solves $p_B\theta_B f'(L_{0B}-\bar{i}) = w+H$. External hiring is $e_A^* > 0$ to ensure that $(p_A+\varepsilon)\theta_A f'(L_{0A}+e_A^*+\bar{i}) = w+H$. Note that $\bar{i} = \widehat{i}(\varepsilon^{nb})$.

We just showed that internal reallocations never exceed the $\bar{i}$ such that $p_B\theta_B f'(L_{0B}-\bar{i}) = w+H$. Therefore, if $\mu L_{0B} \geq \bar{i}$ the constraint never binds, and the optimal adjustment is the one identified above. It follows that the condition $\bar{i} = \mu L_{0B}$ (or equivalently $p_B\theta_B f'(L_{0B}-\mu L_{0B}) = w+H$) defines a threshold level $\overline{\mu}_B$ such that the ILM constraint is slack whenever $\mu \geq \overline{\mu}_B$.

Let us consider now the case in which $\mu < \overline{\mu}_B$, so that $\mu L_{0B} < \bar{i}$. From $\bar{i} = \widehat{i}(\varepsilon^{nb})$ and $\widehat{i}(\varepsilon)$ being strictly increasing in ε, it follows that for any $\mu < \overline{\mu}_B$ there exists a threshold level of the size of the shock, ε_b, with $\varepsilon_b < \varepsilon^{nb}$, such that $\widehat{i}(\varepsilon_b) = \mu L_{0B}$.

For any $\varepsilon \leq \varepsilon_b$ it is that $\widehat{i}(\varepsilon) \leq \mu L_{0B}$ and the equalised marginal revenue products of labor are lower than $w+H$ (the latter follows from $\varepsilon_b < \varepsilon^{nb}$). Therefore, the optimal internal reallocation is $i^*(\varepsilon) = \widehat{i}(\varepsilon)$, the ILM constraint does not bind, and it is optimal not to hire from the external labor market (i.e. $e_A^* = 0, e_B^* = 0$).

Instead, for any $\varepsilon > \varepsilon_b$ it is $\widehat{i}(\varepsilon) > \mu L_{0B}$: the internal reallocation that the equalises the marginal revenue product of labor across the two units exceeds the ILM constraint and, at $i = \mu L_{0B}$, the marginal revenue product of unit A is higher than that of unit B:

$$(p_A+\varepsilon)\theta_A f'(L_{0A}+\mu L_{0B}) > p_B\theta_B f'(L_{0B}-\mu L_{0B})$$

Note that from $\mu < \overline{\mu}$ it follows that $\mu L_{0B} < \bar{i} = \widehat{i}(\varepsilon^{nb})$. Therefore, when $i = \mu L_{0B}$, $p_B\theta_B f'(L_{0B}-\mu L_{0B}) < w+H$ and no external adjustment in unit B (i.e. $e_B^* = 0$) is optimal.

Regarding the external adjustment of unit A, there exists a threshold level of the size of the shock, ε^b, with $\varepsilon^b > \varepsilon_b$, such that $(p_A+\varepsilon^b)\theta_A f'(L_{0A}+\mu L_{0B}) \geq w+H$ iff $\varepsilon \geq \varepsilon^b$.

Therefore, if $\varepsilon \in (\varepsilon_b, \varepsilon^b]$, the optimal adjustment is such that $i^* = \mu L_{0B}$ and $e_A^* = 0$. Instead, if $\varepsilon > \varepsilon^b$, the optimal adjustment is such that $i^* = \mu L_{0B}$ and $e_A^* > 0$. □

The following Corollary derives two important predictions that we test in the paper.

Corollary 1. ***Comparative statics with respect to*** μ
For all $\mu < \overline{\mu}$*, as* μ *increases: (i) the marginal value of the ILM decreases:* $\partial\lambda^*/\partial\mu < 0$*; (ii) the internal reallocation* i^* *increases and substitutes for external hiring (when external hiring is performed):* $\partial i^*/\partial\mu \geq 0$.

Proof. Let us consider first the case in which $\varepsilon \in [\varepsilon_b, \varepsilon^b]$ so that only (constrained) internal adjustments are made in response to the shock. Differentiating the equations in (3b), one obtains:

$$di^* = d\mu L_{0B}$$

and,

$$di^*[(p_A + \varepsilon)\theta_A f''(L_{0A} + e_A^* + i^*) + p_B\theta_B f''(L_{0B} - i^*)] = d\lambda.$$

From the concavity of the production functions it follows that:

$$\frac{di^*}{d\mu} = L_{0B} > 0; \quad \frac{d\lambda}{d\mu} = L_{0B}[(p_A + \varepsilon)\theta_A f''(L_{0A} + e_A^* + i^*) + p_B\theta_B f''(L_{0B} - i^*)] < 0$$

Let us consider now the case in which $\varepsilon > \varepsilon^b$ and (constrained) internal adjustments are combined with external adjustments. Differentiating the equations in (3c) one obtains:

$$di^* = d\mu L_{0B},$$

$$(di^* + de_A^*)(p_A + \varepsilon)\theta_A f''(L_{0A} + e_A^* + i^*) = 0,$$

and

$$d\lambda = p_B\theta_B f''(L_{0B} - i^*)di^*.$$

Again, from the concavity of the production functions it follows that:

$$\frac{di^*}{d\mu} = L_{0B} > 0; \quad \frac{d\lambda}{d\mu} = L_{0B}p_B\theta_B f''(L_{0B} - i^*) < 0$$
$$\frac{de_A^*}{d\mu} = -L_{0B} < 0.$$

□

The following Corollary derives the optimal labor adjustment when the affiliated firm has no ILM Access ($\mu = 0$), as would be the case for an otherwise identical stand-alone firm.

Corollary 2. ***The limit case with no ILM***
If internal labor reallocations are not possible ($\mu = 0$*), the optimal policy is such that unit A adjusts by hiring on the external market unless the shock is small:*

$$\begin{array}{llr} e_A^* = 0,\ i^* = 0, \quad s.t.\ \ (p_A + \varepsilon)\theta_A f'(L_{0A}) < w + H & & if \ \ \varepsilon \in [0, \varepsilon^b) \\ e_A^* > 0,\ i^* = 0, \quad s.t.\ \ (p_A + \varepsilon)\theta_A f'(L_{0A} + e_A^*) = w + H & & if \ \ \varepsilon \geq \varepsilon^b. \end{array}$$

Proof. From the proof of Proposition 1 it follows that, when $\mu = 0$, the threshold level of the shock $\varepsilon_b = 0$. The threshold ε^b is the one such that $(p_A + \varepsilon^b)\theta_A f'(L_{0A}) = w + H$. □

A.3.1 Model extension: ILM adjustment in a three unit group

Consider a business group with three units. As in the baseline model, unit A is hit by a positive shock, while units B and C are not: their revenues are $p_i\theta_i f(L_{0i} - i_{Ai})$ for $i = B, C$. The bilateral ILM flows from unit B and C, respectively, to unit A cannot be larger than the redeployable workforce:

$i_{AB} \leq \mu_B L_{0B}$ and $i_{AC} \leq \mu_C L_{0C}$: a larger value of μ_i may reflect for instance a closer geographical proximity between unit i and unit A. The headquarters solve:

$$\max_{e_A, e_B, i} \quad (p_A + \varepsilon)\theta_A f(L_{0A} + e_A + i_{AB} + i_{AC}) - w(L_{0A} + e_A + i_{AB} + i_{AC}) - He_A +$$
$$+p_B\theta_B f(L_{0B} - i_{AB}) - w(L_{0B} - i_{AB}) + p_C\theta_C f(L_{0C} - i_{AC}) - w(L_{0C} - i_{AC})$$
$$s.t. \quad i_{AB} \leq \mu_B L_{0B} \qquad\qquad i \leq \mu_C L_{0C}$$

Similarly to the two-unit model, the optimal ILM allocation aims to minimize the wedge between marginal revenue products of labor of different units, as illustrated by the Kuhn-Tucker conditions:

$$(p_A + \varepsilon)\theta_A f'(L_{0A} + e_A^* + i_{AB}^* + i_{AC}^*) - p_B\theta_B f'(L_{0B} - i_{AB}^*) - \lambda_B \leq 0 \qquad i_{AB}^* \geq 0 \tag{15a}$$
$$(p_A + \varepsilon)\theta_A f'(L_{0A} + e_A^* + i_{AB}^* + i_{AC}^*) - p_C\theta_C f'(L_{0C} - i_{AC}^*) - \lambda_C \leq 0 \qquad i_{AC}^* \geq 0 \tag{15b}$$

where λ_B and λ_C are the Lagrange multipliers associated with constraints $i_{AB} \leq \mu_B L_{0B}$ and $i_{AC} \leq \mu_C L_{0C}$.

Proposition 2. ***Larger ILM flows from less profitable units***
Assume unit B is ceteris paribus more profitable than unit C ($p_B\theta_B > p_C\theta_C$), but otherwise identical ($L_{0B} = L_{0C}$, $\mu_B = \mu_C$). Then: (i) the optimal ILM allocation after unit A is hit by a positive shock is such that $i_{AC} > i_{AB} \geq 0$; (ii) unit A's ILM access to unit C has a larger value for the group than unit A's ILM access to unit B: $\lambda_C \geq \lambda_B$.

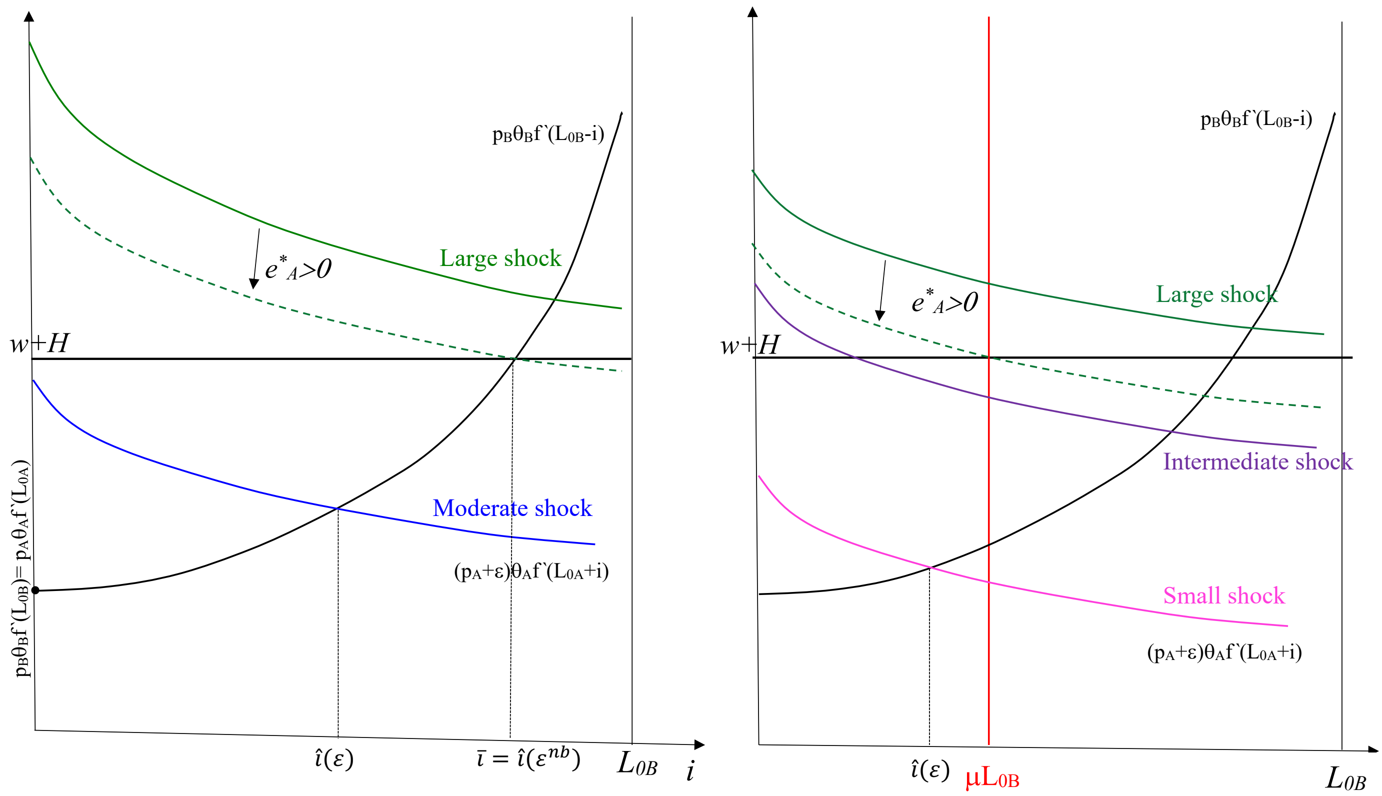
Proof. There are three cases. First, both ILM constraints are slack ($\lambda_B = \lambda_C = 0$); in this case, $MRPL_A(\varepsilon) - MRPL_B \leq 0$ and $MRPL_A(\varepsilon) - MRPL_C \leq 0$. The solution where $i_{AB} > 0$, $i_{AC} = 0$, with $(p_A + \varepsilon)\theta_A f'(L_{0A} + e_A + i_{AB}) = p_B\theta_B f'(L_{0B} - i_{AB}) < p_C\theta_C f_C'(L_{0C})$, is not compatible with $p_B\theta_B > p_C\theta_C$ and can be ruled out. Two solutions are possible: (i) $i_{AB} > 0$, $i_{AC} > 0$, which implies $(p_A + \varepsilon)\theta_A f'(L_{0A} + e_A + i_{AB} + i_{AC}) = p_B\theta_B f'(L_{0B} - i_{AB}) = p_C\theta_C f_C'(L_{0C} - i_{AC})$; as units B and C are otherwise identical but $p_B\theta_B > p_C\theta_C$, it must be $i_{AC} > i_{AB} > 0$; (ii) $i_{AC} > 0 = i_{AB}$, with $(p_A + \varepsilon)\theta_A f'(L_{0A} + e_A + i_{AB}) = p_C\theta_C f_C'(L_{0C} - i_{AC}) \leq p_B\theta_B f'(L_{0B})$.

Second, only one constraint binds. The solution with $\lambda_B > 0$, $\lambda_C = 0$, $i_{AB} = \mu_B L_{0B}$, $i_{AC} \in [0, \mu_C L_{0C})$ would imply: $(p_A+\varepsilon)\theta_A f'(L_{0A}+e_A+\mu_B L_{0B}) = p_B\theta_B f'(L_{0B}-\mu_B L_{0B}) \leq p_C\theta_C f_C'(L_{0C} - i_{AC})$. This is not compatible with $p_B\theta_B > p_C\theta_C$ and can be ruled out. The solution where $\lambda_C > \lambda_B = 0$, $i_{AB} \in [0, \mu_C L_{0C})$, $i_{AC} = \mu_C L_{0C}$ is instead feasible.

Third, both constraints bind: $\lambda_B > 0$, $\lambda_C > 0$, $i_{AB} = \mu_B L_{0B}$, $i_{AC} = \mu_C L_{0C}$. In this case, the Kuhn-Tucker condition writes as: $(p_A+\varepsilon)\theta_A f'(L_{0A}+e_A+\mu_B L_{0B}+\mu_C L_{0C}) = p_B\theta_B f'(L_{0B}-\mu_B L_{0B})+\lambda_B = p_C\theta_C f_C'(L_{0C} - \mu_C L_{0C}) + \lambda_C$. This, together with $p_B\theta_B > p_C\theta_C$, implies that $\lambda_C > \lambda_B$.

$\square$

Figure A1: Graphic Representation of Proposition 1's proof



Note: in both panels, the horizontal axis measures the ILM flow from unit B to unit A, the vertical axis displays the marginal revenue product of labor ($MRPL$) of the two units as a function of internal hiring i, after the shock has hit unit A. The **left hand panel** illustrates the optimal labor adjustment when the ILM constraint does not bind. When the shock is moderate, the ILM allocation that satisfies (2b) is such that $MRPL_A = MRPL_B < w + H$, implying $e_A^* = 0$ by condition (2a). When the shock is large, the intersection between $MRPL_A$ and $MRPL_B$ would occur above $w + H$ (violating (2a)) if no external hiring took place: it is then optimal to engage in external hiring $e_A^* > 0$, which corresponds to a downward shift of the curve $MRPL_A(i)$ to the point where $MRPL_A = MRPL_B = w + H$. The **right hand panel** illustrates the optimal labor adjustment when the ILM is "thin". The ILM constraint does not bind if the shock is small, as the intersection between $MRPL_A$ and $MRPL_B$ occurs at $i^* = \widehat{i}(\varepsilon^{nb}) < \mu L_{0B}$. However, if the shock is intermediate or large, the ILM constraint binds and $i^* = \mu L_{0B}$. Similarly to the unconstrained case, external hiring takes place only in case of a large shock. Note that with the constraint binding, the MRPLs cannot be equalized across the two units: by equation (2b), there is a wedge λ between the marginal revenue product of labor of the shocked and the non-shocked unit. In the Figure, λ is the distance between $MRPL_A$ and $MRPL_B$, measured at $i^* = \mu L_{0B}$, the constrained ILM flow.

A.4 The ILM Response to Positive Shocks

A.4.1 Descriptives on Large Competitor Closures

Table A7. 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.

A.4.2 Descriptive statistics on industries experiencing large closure events

Table A8 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 A8. 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	9,342.3	2,300.1			
143Z	Mining of chemical and fertilizer minerals	2007	1,198.3				
151C	Processing/preserving of poultry meat	2004	1,357.5				
151F	Cooked meats production/trade	2006	533				
155C	Manufacture of cheese	2009	814.5	1,748.5			
155D	Manufacture of other dairy products	2008	625.5				
157C	Manufacture of pet food	2008	2,358.5				
158A	Industrial manufacture of bread and fresh pastry	2005	1,373				
158H	Manufacture of sugar	2009	1,689.5				
158V	Manufacture of prepared meals	2006	1,231.5				
159J	Manufacture of cider/other fruit wines	2005	868.7				
159S	Production of mineral water	2005	4,339.7				
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	1,265.3			
212E	Other printing	2008	1,332.7			
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	1,480.5			
244A	Manufacture of basic pharmaceutical products	2007	3,771.3			
251E	Manufacture of other rubber products	2007	1,655.3	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	1,166.7			
275A	Casting of iron	2004	848			
282D	Manufacture of central heating radiators and boilers	2006	1,079.8			
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	1,244.5			
316A	Manufacture of electric lighting equipment	2009	1,279.5			
316D	Manufacture of other technical ceramic products	2005	1,102.5			
321C	Manufacture of loaded electronic boards	2009	1,700.7			
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	2,311.8			

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	1,058.5				
503A	Wholesale of motor vehicle parts and accessories	2007	851.3				
511R	Agents specialized in the sale of other particular products	2008	1,083				
512A	Wholesale of grain, unmanufactured tobacco, seeds and animal feeds	2009	771				
515C	Wholesale of metals and metal ores	2008	1,217				
518G	Wholesale of computers, computer peripheral equipment and software	2009	852				
518L	Wholesale of electric equipment	2007	1,353	655	1,074	1,212	1,222
521A	Retail sale of fruit and vegetables in specialized stores	2007	1,893.8				
524H	Retail sale of furniture	2008	563				
526B	Retail sale via home-shopping by specialized catalogue	2008	767				
526G	Door to door sale	2006	1,578.7				
526H	Vending machine sale	2006	1,065.2				
552E	Holiday and other short-stay accommodation	2009	541.7	1447,7			
553B	Fast food restaurants	2008	3,380.2				
555A	Other catering services	2004	2,795	1,284			
555C	Collective catering under contract	2007	1,064	650.2	8,096.8		
602B	Regular road transport of passengers	2007	1,740.5	593			
602M	Interurban freight transport by road	2009	619.7				
602P	Rent of lorries with driver	2003	1,242.2				
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	1,200.7	771.2			
741G	Management consultancy activities	2009	524.5				
743B	Technical analyses, testing and inspections	2006	1,063.5				
748B	Photographic activities	2009	684.5	2004	986.5		
748D	Packaging activities	2008	587.2				

900G	Collection of non-hazardous waste	2009	542.5					

A.4.3 ILM response to positive shocks: Tables

This sections reports the results on the share of internal hires and other firm-level outcomes illustrated in Section 5.1.

Table A9. Descriptive Statistics of Regression Sample

	Mean	**St.dev.**	**p10**	**p50**	**p90**	**N**
Shocked BG firms (firm-year observations)						
Firm size (empl.)	128.89	555.13	2	27	2,227.5	51,632
Market shares	0.007	0.034	0.0001	0.0006	0.01	51,632
Investment	837.1	6,483.9	0	36	1,156.42	51,632
Share of internal hires	0.061	0.193	0	0	0.17	45,330
Shocked firms' group (group-year observations)						
Group Size	862.12	6,441.28	10.3	60.7	822.8	47,221
Number of other affiliates	7.69	37.90	1	2.57	10.64	47,221
Number of 4-digit industries	3.39	5.56	1	2	5.8	47, 286
Number of regions	1.82	2.09	1	1	3.2	47,153
HHI (4-digit industries)	0.77	0.22	0.454	0.83	1	47,146
HHI (Regions)	0.88	0.20	0.561	1	1	47,153

Note: *Firm size* is measured as the total number of (full time equivalent) employees; *Investment* equals CapEx in 1000 EUR. *Market share* is the ratio of firm j's sales over total sales in its four-digit shocked industry s. *Share of internal hires* is the ratio of new hires originating from same-group firms over total hiring of firm j. *Group size* is measured as the total number of (full time equivalent) employees in firm j's group. A group's *HHI (4-digit industries/Regions)* is computed as 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 4-digit industry/region to total group employment.

Table A10. Impact of large competitor closures on firm-level outcomes

Distance from the shock	Market shares	Employment	Hiring	Investment	N	Share of internal hires	N
-3	0.00018	-4.00036	0.80413	38.08109	5,304	-0.00095	4,814
	(0.00024)	(2.74736)	(1.36694)	(76.64511)		(0.00388)	
-2	0.00003	-2.97873	-0.97907	64.87894	5,992	0.00220	5,782
	(0.00013)	(1.60254)	(0.88286)	(56.35746)		(0.00256)	
-1	-	-	-	-	6,863	-	6,188
	-	-	-	-		-	
0	0.00054^{*}	8.95575^{**}	4.82051	29.32352	6,642	0.00322	6,157
	(0.00021)	(2.73665)	(2.46180)	(109.62686)		(0.00256)	
1	0.00063^{*}	14.62089^{**}	3.69476	373.08798	6,605	0.01032^{***}	5,871
	(0.00026)	(4.50747)	(1.96280)	(204.12998)		(0.00313)	
2	0.00057^{*}	11.50877^{*}	-0.04367	137.87057	4,718	0.01468^{**}	3,603
	(0.00029)	(4.81754)	(1.36309)	(88.30299)		(0.00535)	
3	0.00058	7.15773	-1.30303	66.34261	2,315	0.00342	1,801
	(0.00034)	(5.29684)	(1.75801)	(106.47428)		(0.00566)	
N	51632					45513	

Note: The table reports the coefficients $\widehat{\alpha}_\tau - \widehat{\alpha}_{-1}$ 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 different columns refer to the outcomes indicated in the top row: employment; hiring; capital expenditure (in 1,000 Euros); market share (in sales); fraction of internal hiring over total hiring. Standard errors in parenthesis are clustered at the industry and group level. Significance levels are * 5%, ** 1%, *** 0.1%.

A.4.4 Expansion by ILM Access: Tables

This sections reports the results on the expansion of shocked BG firms with different levels of *ILM Access*, illustrated in Section 5.2.

Table A11. Average pre-event outcomes of positively shocked firms

ILM Access	Employment	N	Investment	N	Market Shares	N	$NAIP$	N	Share of internal hires	N
Below Median	75.402	9,019	435.543	9,019	0.0044	9,019	0.062	11,775	0.026	7,926
	(194.135)		(2,053.158)		(0.02)		(0.353)		(0.132)	
Above Median	171.638	9,140	1,083.265	9140	0.0086	9,140	0.358	12,332	0.092	8,802
	(690.54)		(6,011.3)		(0.037)		(1.631)		(0.229)	
Top Quartile	269.606	4,418	1,773.491	4,418	0.0138	4,418	0.575	6,081	0.120	4,389
	(957.52)		(8,254.93)		(0.049)		(2.231)		(0.251)	
Top Decile	492.790	1,730	2,886.628	1,730	0.0222	1,730	1.093	2,383	0.145	1,907
	(1,436.72)		(10,411.74)		(0.057)		(3.392)		(0.256)	
95th Percentile	670.113	844	4,176.980	844	0.0299	844	1.758	1,185	0.165	1,006
	(1,830.078)		(13,889.07)		(0.065)		(4.584)		(0.258)	

Note: The table reports the average pre-event outcomes of BG firms that experience a positive shock (a large competitor closure) in 2002-2010. The outcomes reported are employment, capital expenditure (in 1000 Euros), market share (in sales), number of active internal partners and share of internal hires. All 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 outcomes 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.

Table A12. Share of internal hires and number of active internal partners by ILM Access

	Share of internal hires				Number of active internal partners			
	ILM Access							
	(1)		(2)		(3)		(4)	
Distance from the shock	Below Median	N	Above Median	N	Below Median	N	Above Median	N
-3	-0.00356	2,253	0.00096	2,532	-0.00931	3,553	-0.04160*	3,732
	(0.00370)		(0.00619)		(0.00643)		(0.01800)	
-2	-0.00086	2,716	0.00486	3,039	-0.00181	3,994	-0.00187	4,220
	(0.00322)		(0.00410)		(0.00587)		(0.01382)	
-1		2,957	-	3,231	-	4,228	-	4,380
	-	-	-	-	-	-	-	-
0	0.00112	2,904	0.00577	3,243	0.00492	4,228	0.03446***	4,380
	(0.00269)		(0.00431)		(0.00518)		(0.00973)	
1	0.00112	2,801	0.01924**	3,057	0.00485	4,228	0.04807**	4,379
	(0.00269)		(0.00590)		(0.00539)		(0.01471)	
2	0.00529	1,747	0.02359**	1,847	0.00405	2,966	0.03074	2,863
	(0.00430)		(0.00910)		(0.00729)		(0.02102)	
3	-0.00292	931	0.00940	867	-0.01270	1,481	-0.02912	1,308
	(0.00322)		(0.01098)		(0.00710)		(0.02462)	
Firm FE	YES							
N	45,330				68,864			

Note: The table reports the effects of large competitor closures on the *share of internal hires* and *number of active internal partners* 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 from event date -1 to event date $\tau \in [-3, +3]$, for shocked firms with below median/above median *ILM Access*. The median value of *ILM Acces* is equal to 1 worker. We include firm fixed effects and year dummies in our specification. Standard errors in parenthesis are clustered at the industry and group level. Coefficient in columns (1) and (2) are significantly difference at 1% at $\tau = 1$ ($p = 0.0086$), and at 5% at $\tau = 2$ ($p = 0.0572$). Coefficients in columns (3) and (4) are significantly different at 5% at $\tau = 0$ ($p = 0.011$) and at 1% at $\tau = 1$ ($p = 0.008$). *** denotes significance at the 0.1% level; ** denotes significance at the 1% level; * denotes significance at the 5% level

Table A13. Impact of large competitor closures on shocked firms employment, by ILM Access

	ILM Access												
	(1)		(2)		(3)	(4)		(5)	(6)		(7)	(8)	
Distance from the shock	Below Median	N	Above Median	N	Below Median	Top Quartile	N	Below Median	Top Decile	N	Below Median	95th percentile	N.
-3	-3.10290	2,640	-5.67817	2,664	-3.10290	-12.37541	1,264	-3.10290	-23.57419	490	-3.10290	-49.44023	235
	(1.64645)		(5.40430)		(1.64659)	(10.28419)		(1.64694)	(25.05490)		(1.64711)	(46.35161)	
-2	-1.90550	2,990	-3.98182	3,002	-1.90550	-9.43921	1,442	-1.90550	-21.43636	559	-1.90550	-32.94194	271
	(1.22326)		(3.17796)		(1.22337)	(6.06288)		(1.22363)	(14.70611)		(1.22376)	(25.75706)	
-1	-	3,389	-	3,474	-	-	1,712	-	-	681	-	-	338
	-		-		-	-		-	-		-	-	
0	1.43090	3,304	16.37498***	3,338	1.43090	30.57516***	1,635	1.43090	63.98161***	645	1.43090	58.05572*	318
	(1.52487)		(4.83166)		(1.52500)	(8.36953)		(1.52532)	(18.80257)		(1.52548)	(28.09654)	
1	0.98381	3,281	28.98158***	3,324	0.98381	53.44117***	1,618	0.98381	109.38349***	634	0.98381	126.43472*	312
	(1.79313)		(8.18784)		(1.79329)	(13.74126)		(1.79367)	(27.75162)		(1.79386)	(49.56476)	
2	-0.19311	2,256	23.44408**	2,462	-0.19311	42.38592**	1,168	-0.19311	77.77572**	476	-0.19311	67.34976	243
	(1.66076)		(8.83710)		(1.66091)	(14.53910)		(1.66126)	(28.01626)		(1.66143)	(50.33089)	
3	-3.16743	1,152	17.40859	1,163	-3.16743	33.44341*	555	-3.16743	63.82465*	240	-3.16743	38.05846	127
	(1.66177)		(9.83262)		(1.66192)	(16.44800)		(1.66227)	(30.81406)		(1.66244)	(56.59013)	
Firm FE	YES				YES			YES			YES		
N	51,632				39,653			32,180			29,704		

Note: The table reports the effects of large competitor closures on employment 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 A14. Impact of large competitor closures on shocked firms investment, by ILM Access

	ILM Access							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Distance from the shock	Below Median	Above Median	Below Median	Top Quartile	Below Median	Top Decile	Below Median	95th percentile
-3	19.00091	42.32500	19.00091	183.69113	19.00091	434.57565	19.00091	505.09186
	(32.94442)	(165.85087)	(33.41211)	(304.16166)	(35.29589)	(363.28045)	(35.19228)	(680.06438)
-2	27.75934	92.98137	27.75934	164.48001	27.75934	163.37979	27.75934	249.69312
	(27.97765)	(107.98447)	(28.07689)	(205.87528)	(28.86550)	(280.96878)	(28.52117)	(545.51656)
-1	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-
0	-31.65490	49.14845	-31.65490	153.16983	-31.65490	531.30594	-31.65490	520.79584
	(54.11254)	(188.06985)	(54.14050)	(329.70699)	(54.07079)	(525.02231)	(54.13082)	(974.70101)
1	71.38689	705.58015	71.38689	1.31e+03	71.38689	1.39e+03**	71.38689	2.01e+03*
	(62.69774)	(414.69698)	(63.14897)	(788.79146)	(62.78192)	(486.11287)	(65.62204)	(834.31963)
2	-10.74781	277.58040	-10.74781	491.81888	-10.74781	881.22055*	-10.74781	800.46466
	(51.06208)	(154.93814)	(51.29193)	(281.51685)	(51.22201)	(430.88550)	(54.89769)	(717.34284)
3	-92.95987	206.58598	-92.95987	422.89243	-92.95987	521.57541	-92.95987	459.88556
	(51.73536)	(201.41968)	(51.86227)	(378.04053)	(53.62720)	(528.90343)	(53.52520)	(944.86672)
Firm FE	YES		YES		YES		YES	
N	51,632		39,653		32,180		29,704	

Note: The table reports the effects of large competitor closures on investment (CapEx) 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. Coefficients in columns (5) and (6) are significantly different at 1% at $\tau = 1$ ($p = 0.0067$) and at 5% at $\tau = 2$ ($p = 0.035$). Coefficients in columns (7) and (8) are significantly different at 5% at $\tau = 1$ ($p = 0.0209$). Standard errors in parenthesis are clustered at the industry and group level. Significance levels are * 5%, ** 1%, *** 0.1%.

Table A15. Impact of large competitor closures on shocked firms market shares, by ILM Access

	ILM Access							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Distance from the shock	Below Median	Above Median	Below Median	Top Quartile	Below Median	Top Decile	Below Median	95th percentile
-3	0.00009	0.00025	0.00009	0.00035	0.00009	-0.00069	0.00009	-0.00309
	(0.00023)	(0.00041)	(0.00023)	(0.00077)	(0.00023)	(0.00138)	(0.00023)	(0.00234)
-2	0.00008	-0.00002	0.00008	-0.00010	0.00008	-0.00103	0.00008	-0.00265
	(0.00012)	(0.00024)	(0.00012)	(0.00046)	(0.00012)	(0.00082)	(0.00013)	(0.00143)
-1	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-
0	-0.00007	0.00120***	-0.00007	0.00215***	-0.00007	0.00426**	-0.00007	0.00514**
	(0.00028)	(0.00034)	(0.00028)	(0.00063)	(0.00028)	(0.00130)	(0.00028)	(0.00165)
1	-0.00018	0.00152***	-0.00018	0.00276***	-0.00018	0.00549***	-0.00018	0.00750***
	(0.00032)	(0.00043)	(0.00032)	(0.00080)	(0.00032)	(0.00151)	(0.00032)	(0.00213)
2	-0.00022	0.00141**	-0.00022	0.00251**	-0.00022	0.00511***	-0.00022	0.00687**
	(0.00034)	(0.00047)	(0.00034)	(0.00087)	(0.00034)	(0.00153)	(0.00034)	(0.00231)
3	0.00000	0.00115*	0.00000	0.00203	0.00000	0.00344	0.00000	0.00325
	(0.00032)	(0.00058)	(0.00032)	(0.00109)	(0.00032)	(0.00178)	(0.00032)	(0.00251)
Firm FE	YES		YES		YES		YES	
N	51,632		39,653		32,180		29,704	

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 A16. Impact of large competitor closures on employment and market shares, by group industry-diversification

	(1)	(2)	(3)	(4)
Distance from the shock	Market shares		Employment	
	Below Median	Above Median	Below Median	Above Median
-3	0.00000	0.00040	-1.01357	-8.38817
	(0.00017)	(0.00046)	(2.00046)	(5.05485)
-2	0.00002	0.00010	-0.21684	-6.42105*
	(0.00009)	(0.00025)	(1.51967)	(3.08641)
-1	-	-	-	-
	-	-	-	-
0	0.00035*	0.00075	7.54611*	10.98859**
	(0.00015)	(0.00041)	(3.37936)	(3.66388)
1	0.00027	0.00102	9.59197	21.02004***
	(0.00016)	(0.00052)	(5.09680)	(6.26882)
2	0.00018	0.00097	6.35588	18.24756*
	(0.00018)	(0.00058)	(5.27712)	(7.13891)
3	0.00016	0.00100	2.85549	13.22330
	(0.00019)	(0.00067)	(6.04922)	(7.79299)
Firm FE	YES		YES	
N	50,782		50,782	

Note: The table shows the effect of a large competitor closure on shocked BG firms' Market Share and Employment, depending on the group's industry diversification (see Figure 10). We measure (pre-shock) group industry diversification as the opposite of the group-level HHI, i.e. an HHI based on the employment shares in the different four-digit industries in which group affiliates operate at $\tau = -1$. The different columns refer to the outcomes indicated in the top row. Standard errors in parenthesis are clustered at the industry and group level. Significance levels are * 5%, ** 1%, *** 0.1%.

Table A17. Impact of large competitor closures on employment and market shares of high-*ILM Access* firms, by group cash

	(1)	(2)	(3)	(4)
Distance from the shock	Market shares		Employment	
	Below Median	Above Median	Below Median	Above Median
-3	0.00029	0.00047	-9.23177	-4.05791
	(0.00071)	(0.00061)	(7.42153)	(7.71596)
-2	-0.00067	0.00031	-12.78216*	-0.97398
	(0.00038)	(0.00040)	(4.98703)	(4.11511)
-1	-	-	-	-
	-	-	-	-
0	0.00121	0.00133**	23.69436*	13.89661**
	(0.00066)	(0.00042)	(10.76387)	(4.55316)
1	0.00144	0.00190**	33.58362**	33.43713**
	(0.00077)	(0.00061)	(11.97600)	(10.28180)
2	0.00127	0.00188**	26.86433*	31.44790**
	(0.00089)	(0.00066)	(11.23107)	(11.60597)
3	0.00163	0.00169*	18.38376	25.26248*
	(0.00138)	(0.00067)	(15.57232)	(12.58672)
Firm FE	YES		YES	
N	24,107		24,107	

Note: The table shows the effect of a large competitor closure on shocked BG firms' Market Share and Employment (for firms with ILM Access above median), depending on group cash (see Figure 10). Group cash equals total cash over total assets of all subsidiaries affiliated with shocked BG firm j. The different columns refer to the outcomes indicated in the top row. Standard errors in parenthesis are clustered at the industry and group level. Significance levels are * 5%, ** 1%, *** 0.1%.

A.4.5 Bilateral flows

This sections reports the results on bilateral flows of workers illustrated in Section 5.3.

Table A18. Pairs of firms with destination firm subject to positive shock in 2002-2010

Year	External Pairs	Same-Group Pairs	Total
2003	330,183	6,868	337,051
2004	351,440	7,295	358,753
2005	373,308	7,676	380,984
2006	386,449	8,007	394,456
2007	392,429	8,257	400,686
2008	383,764	8,091	391,855
2009	365,841	7,697	373,538
2010	334,381	6,863	341,244
Total	2,917,795	60,754	2,978,549

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 A19. Average bilateral 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	532,768	11,598	530,589	11,385	530,589	11,385	530,589	11,385	530,589	11,385
$[-3, 0)$	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	1,048,675	22,402	1,044,834	21,961	1,044,834	21,961	1,044,834	21,961	1,044,834	21,961
$[0, 3]$	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	1,175,735	24,123	1,170,861	23,667	1,170,861	23,667	1,170,861	23,667	1,170,861	23,667
≥ 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	160,617	2,631	160,353	2,585	160,353	2,585	160,353	2,585	160,353	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 A20. Impact of large competitor closures on worker flows from ELM and ILM firms

	Baseline			
	(1)		(2)	
Distance from shock	External flows	N	Internal flows	N
-3	0.00019	304,765	0.00436	6,345
	(0.00021)		(0.00277)	
-2	0.00019	354,343	0.00274	7,727
	(0.00012)		(0.00207)	
-1	-	389,567	-	8,330
	(-)		(-)	
0	0.00025**	386,415	0.00517*	8,293
	(0.00009)		(0.00230)	
1	0.00016	376,977	0.01167***	7,986
	(0.00019)		(0.00294)	
2	-0.00026	276,233	0.01543**	5,516
	(0.00026)		(0.00525)	
3	-0.00022	136,110	0.01603***	2,328
	(0.00033)		(0.00439)	
Pair FE	Yes			
N	2,975,794			

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). 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 A18); however, 2755 are singletons and do not contribute to the estimation of the coefficients.

Table A21. Impact of large competitor closures on worker flows from ELM and ILM firms, same/different local labor market and industry

	Same Zone d'emploi		Different 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	0.00057	0.00575	0.00012	0.00362	0.00052**	0.00610	0.00031	-0.00411
	(0.00082)	(0.00535)	(0.00030)	(0.00357)	(0.00017)	(0.00600)	(0.00103)	(0.00438)
-2	0.00024	0.00325	0.00011	0.00123	0.00010	0.00836*	0.00088	-0.00654
	(0.00055)	(0.00345)	(0.00016)	(0.00261)	(0.00020)	(0.00356)	(0.00097)	(0.00336)
-1	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-
0	0.00024	0.00111	-0.00008	0.00839**	0.00015	0.01202**	-0.00148	-0.00060
	(0.00068)	(0.00400)	(0.00030)	(0.00300)	(0.00013)	(0.00387)	(0.00159)	(0.00391)
1	-0.00106	0.01195**	0.00043	0.01144***	0.00051	0.01333**	-0.00020	0.00879*
	(0.00116)	(0.00447)	(0.00070)	(0.00283)	(0.00029)	(0.00517)	(0.00160)	(0.00442)
2	-0.00172*	0.01782*	0.00007	0.01389**	-0.00013	0.02342***	0.00178	0.00288
	(0.00081)	(0.00760)	(0.00054)	(0.00521)	(0.00035)	(0.00495)	(0.00161)	(0.00521)
3	-0.00207	0.01585*	-0.00045	0.01565**	-0.00023	0.01308**	0.00177	0.01702*
	(0.00106)	(0.00771)	(0.00055)	(0.00545)	(0.00044)	(0.00494)	(0.00204)	(0.00718)
Pair FE	Yes				Yes			
N	2,455,683				2,382,528			

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 the same local labor market as firm j (estimates displayed in columns (1)-(2)) and flows within pairs where the firm of origin operates in a different local labor market than 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 A22. 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	57,696		57,835	

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 A23. Impact of large competitor closures on employment and market shares by VA per worker of least productive BG affiliates

	(1)	(2)	(3)	(4)
Distance from the shock	Market shares		Employment	
	Below Median	Above Median	Below Median	Above Median
-3	0.00026	0.00040	-12.75023	1.69711
	(0.00065)	(0.00041)	(9.87591)	(3.02550)
-2	-0.00004	0.00001	-8.26947	-0.59974
	(0.00043)	(0.00014)	(5.68288)	(2.22039)
-1	-	-	-	-
	-	-	-	-
0	0.00170**	0.00079*	25.65900**	5.62240*
	(0.00053)	(0.00035)	(9.01450)	(2.81697)
1	0.00220**	0.00098*	47.89453***	7.49502*
	(0.00068)	(0.00041)	(14.41759)	(3.79006)
2	0.00210**	0.00088*	39.04824*	4.52164
	(0.00075)	(0.00045)	(15.54700)	(4.20941)
3	0.00184*	0.00087	34.77898*	-3.19810
	(0.00088)	(0.00058)	(16.89850)	(4.69818)
Firm FE	YES		YES	
N	24,123		24,123	

Note: The table reports the effect of a large competitor closure on shocked BG firms' Market Shares and Employment depending on the (pre-shock) VA per Worker of the least productive affiliate of the rest of the group (see Figure 13). The different columns refer to the outcomes indicated in the top row. The coefficients in columns (1) and (2) are significantly different at 10% at $\tau = 0$ ($p = 0.11$) and $\tau = 1$ ($p = 0.09$). The coefficients in columns (3) and (4) are significantly different at 5% at $\tau = 0$ ($p = 0.033$), at 1% at $\tau = 1$ ($p = 0.0057$), $\tau = 2$ ($p = 0.0029$) and $\tau = 3$ ($p = 0.0025$). Standard errors in parenthesis are clustered at the industry and group level. Significance levels are * 5%, ** 1%, *** 0.1%.

Table A24. 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	11,853,776							

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 (6). 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 A25. Impact of large competitor closures on worker flows from ELM and ILM firms, for selected occupation sub-categories

	STEM-skilled Managers		Admin 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	14,817,220							

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 (6) on 10 occupation subcategories. We split each category in the DADS (see Table A.1) into subgroups. "Managers/high skilled" is divided into: STEM-skilled (Science, Technology, Engineering and Maths) 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. We report here the results for the following four subcategories: STEM-skilled Managers (columns (1)-(2)); Admin 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%.

A.5 Alternative DiD estimators

Recent research has shown that in complicated designs (e.g. with many cohorts and periods), TWFE estimators are biased for the average treatment effect even if parallel trends hold. Indeed, if treatment effects are heterogeneous between cohorts and/or over time, the TWFE estimand identifies a weighted sum of the treatment effects in every cohort and time period, where the weights do not reflect the proportion that a cohort-time cell accounts for in the total population. Weights may even be negative, implying that the TWFE estimand can have a different sign from the underlying treatment effect. The negative weights come from the fact that the TWFE estimator can potentially rely on "forbidden comparisons" (Goodman-Bacon (2021)) using as controls units belonging to cohorts that have already been treated. Novel estimators proposed in the literature choose control groups in a way to avoid using the "forbidden comparisons" that make TWFE estimators not robust to the presence of heterogeneous treatment effects (see de Chaisemartin and D'Haultfœuille (2022) for a survey).

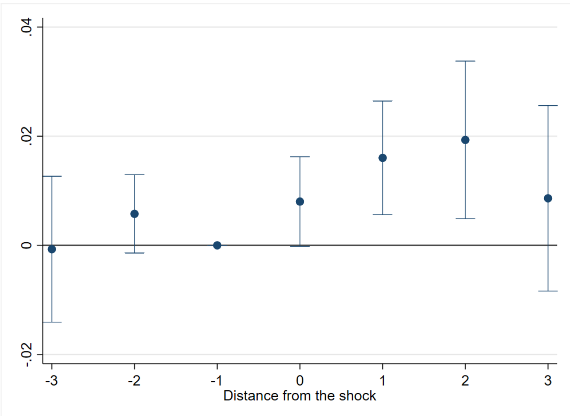
In our setting, a pooled event-study design *à la* Cengiz, Dube, Lindner, and Zipperer (2019) with variation in treatment timing, treatment effect heterogeneity can also lead to negative weights and biased estimates. For this reason, we check the robustness of our results using two recently proposed estimators that are robust to treatment effect heterogeneity.

We first rely on the IW estimator proposed by Sun and Abraham (2021), that is specifically devised for event study designs with binary treatment and staggered rollout, that is, designs where the timing of the treatment differs across cohorts. In cases like ours, where all cohorts get treated at some point in time, their estimator uses the last treated cohort as control. The IW estimator is a convex combination of local effects, and therefore is robust to treatment effect heterogeneity.

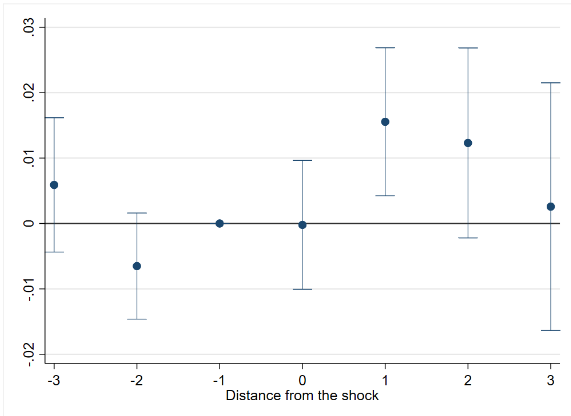
de Chaisemartin and D'Haultfœuille (2020) propose an estimator designed for a staggered binary rollout setting ruling out dynamic effects. Their estimator compares the outcome evolution of switchers to the outcome evolution of groups that are yet to be treated (or never treated), thus avoiding the contamination of time-varying treatment effects. We present additional robustness results based on a recent adaptation of their estimator that allows for dynamic effects (see de Chaisemartin and D'Haultfœuille (2021)).

In the paper, we present results using the pooled event-study design *à la* Cengiz, Dube, Lindner, and Zipperer (2019) as the baseline and verify the robustness to the use of alternative estimators. As highlighted by de Chaisemartin and D'Haultfœuille (2022), "it is still unclear whether researchers should systematically abandon TWFE estimators" which "often have a lower variance than heterogeneity-robust estimators". The case for presenting results from a standard estimator as the baseline is stronger for less complicated settings with binary and staggered rollout treatment like ours where, as conjectured by de Chaisemartin and D'Haultfœuille (2022), the difference with "alternative estimators is likely to be smaller than in more complicated designs (e.g. a non-binary treatment that can turn on and off multiple times, or several treatments)".

Figure A2: Impact of competitors' closures on shocked BG firms' share of internal hires



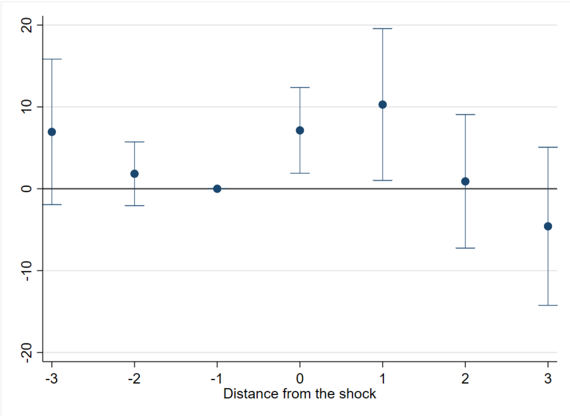
(a) Sun & Abraham (2021)



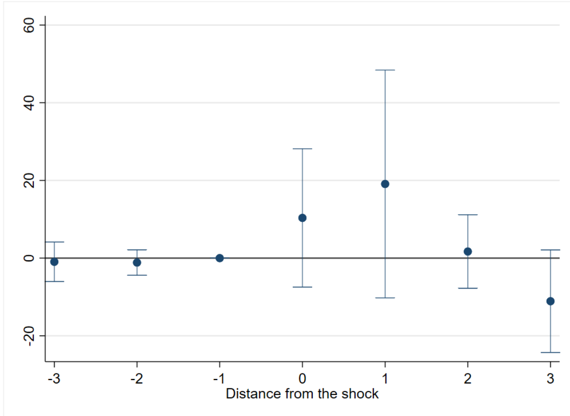
(b) de Chaisemartin & D'Haultfœuille (2021)

Note: Panel (a) plots estimates for the dynamic effect of positive shocks on BG firms' *Share of internal hires*, using Sun and Abraham (2021)'s IW estimator implemented using the STATA package `eventstudyinteract`. Panel (b) uses instead the estimator proposed by de Chaisemartin and D'Haultfœuille (2020) recently adapted to allow for dynamic effects (see de Chaisemartin and D'Haultfœuille (2021)). We implement this estimator using the STATA package `did_multiplegt`. Event date 0 is the year of the 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. The *Share of internal hires* is the ratio of new hires that originate from same-group firms over total hiring of firm j. Table A26 reports the estimated coefficient, s.e., sample size.

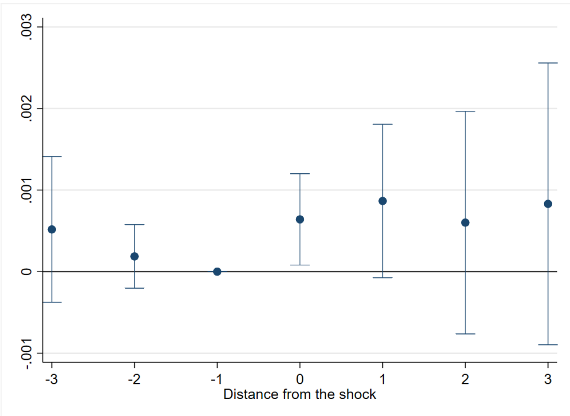
Figure A3: Impact of competitors' closures on shocked BG firms' Employment and Market Share



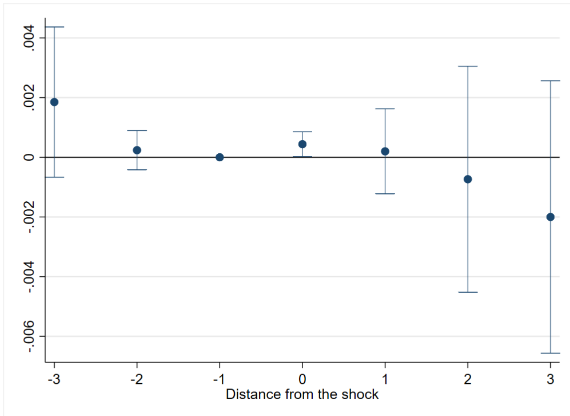
(a) Employment, Sun & Abraham (2021)



(b) Employment, de Chaisemartin & D'Haultfœuille (2021)



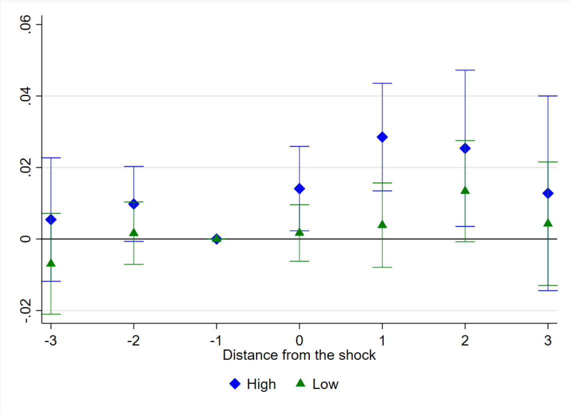
(c) Market Share, Sun & Abraham (2021)



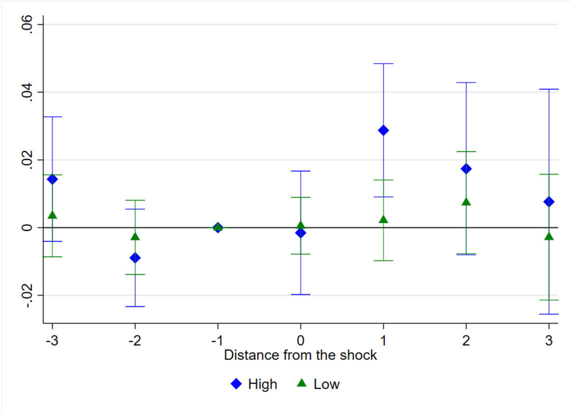
(d) Market Share, de Chaisemartin & D'Haultfœuille (2021)

Note: Panels (a) and (c) plot estimates for the dynamic effect of positive shocks on firm-level outcomes (*Employment* and *Market share*), using Sun and Abraham (2021)'s IW estimator implemented using the STATA package `eventstudyinteract`. Panels (b) and (d) uses instead the estimator proposed by de Chaisemartin and D'Haultfœuille (2020) recently adapted to allow for dynamic effects (see de Chaisemartin and D'Haultfœuille (2021)). We implement this estimator using the STATA package `did_multiplegt`. The error bars show the 95% confidence intervals calculated using standard errors that are clustered at the industry and group level. *Employment* equals the total number of (full-time equivalent) employees of (shocked) firm j. *Market share* is the ratio of firm j's sales over total sales in the same four-digit shocked industry s. Table A26 reports the estimated coefficient, s.e., sample size.

Figure A4: Impact of competitors' closures on shocked BG firms' Share of internal hires by ILM Access



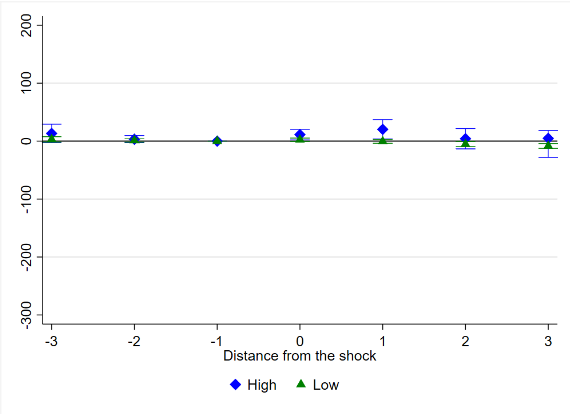
(a) Sun & Abraham (2021)



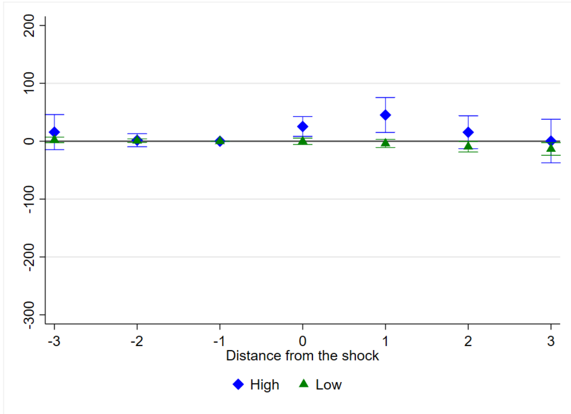
(b) de Chaisemartin & D'Haultfœuille (2021)

Note: Panel (a) plots estimates for the dynamic effect of positive shocks on on BG firms' *Share of internal hires*, depending on the level of *ILM Access*. We use Sun and Abraham (2021)'s IW estimator implemented using the STATA package `eventstudyinteract`. Panels (b) uses instead the estimator proposed by de Chaisemartin and D'Haultfœuille (2020) recently adapted to allow for dynamic effects (see de Chaisemartin and D'Haultfœuille (2021)). We implement this estimator using the STATA package `did_multiplegt`. *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 j; (iii) in a different 4-digit industry than j. The median value of *ILM Acces* is equal to 1 worker. 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 the *Share of internal hires* from event date -1 to event dates $\tau \in [-3, +3]$ (relative to the counterfactual) for firms with *ILM Access* above the median. The green triangles represent the change in the *Share of internal hires* for firms with below median *ILM Access*. The error bars show the 95% confidence intervals calculated using standard errors that are clustered at the industry and group level. The *Share of internal hires* is the ratio of new hires that originate from same-group firms over total hiring of firm j. Table A27 reports the estimated coefficient, s.e., sample size.

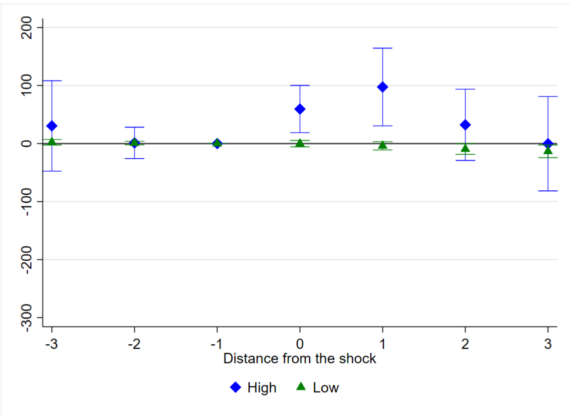
Figure A5: Impact of competitors' closures on shocked BG firms' employment by ILM access – Sun & Abraham (2021)



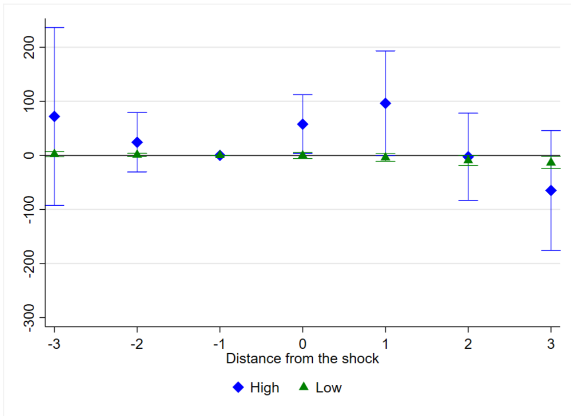
(a) ILM Access above median vs. below median



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



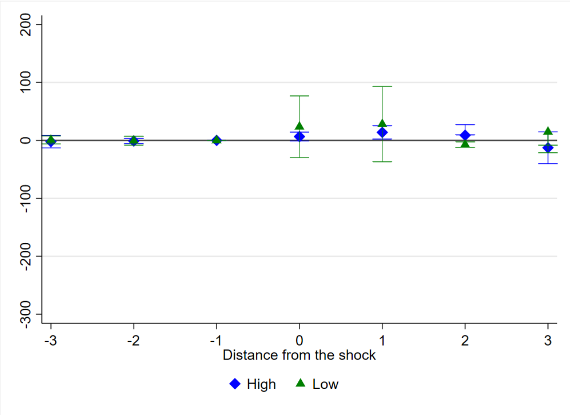
(c) ILM Access above median vs. below median



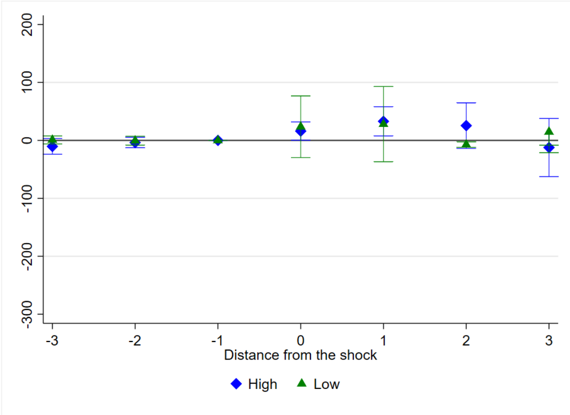
(d) ILM Access in top quartile vs. below median

Note: Panels (a)-(d) plots estimates for the dynamic effect of positive shocks on BG firms' employment, depending on the level of *ILM Access*. We use Sun and Abraham (2021)'s IW estimator implemented using the STATA package `eventstudyinteract`. *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 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 employment from event date -1 to event dates $\tau \in [-3, +3]$ (relative to the counterfactual) 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 employment for firms with below median *ILM Access*. The median value of *ILM Access* 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. Table A28 reports the estimated coefficient, s.e., sample size.

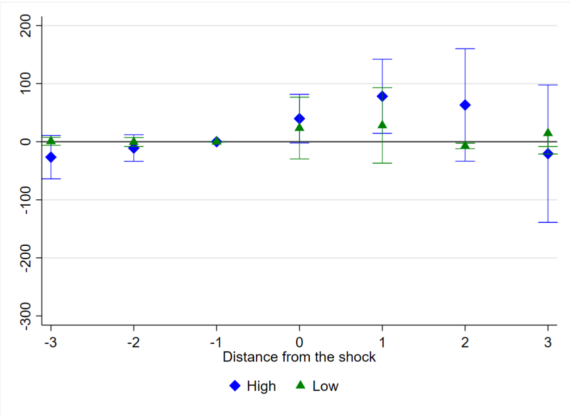
Figure A6: Impact of competitors' closures on shocked BG firms' employment by ILM access – de Chaisemartin & D'Haultfœuille (2021)



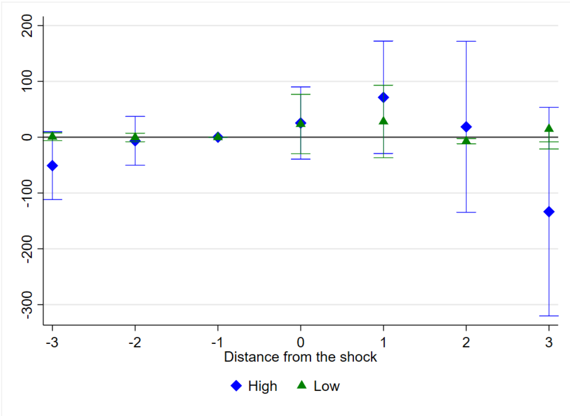
(a) ILM Access above median vs. below median



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



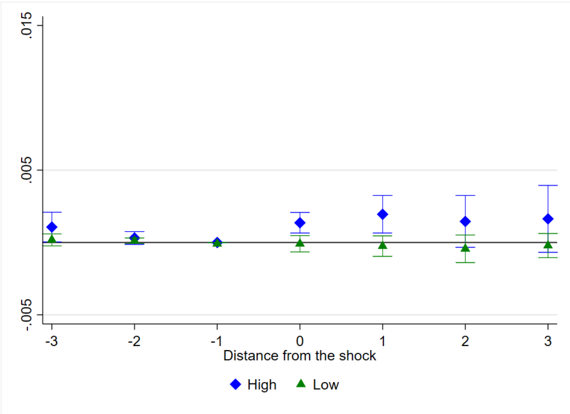
(c) ILM Access above median vs. below median



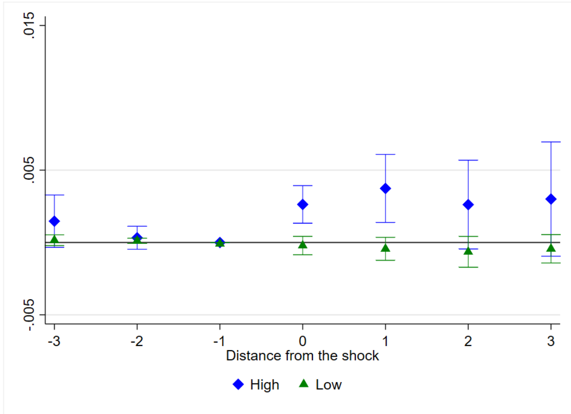
(d) ILM Access in top quartile vs. below median

Note: Panels (a)-(d) plots estimates for the dynamic effect of positive shocks on BG firms' employment, depending on the level of *ILM Access*. We uses the estimator proposed by de Chaisemartin and D'Haultfœuille (2020) recently adapted to allow for dynamic effects (see de Chaisemartin and D'Haultfœuille (2021)). We implement this estimator using the STATA package `did_multiplegt`. *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 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 employment from event date -1 to event dates $\tau \in [-3, +3]$ (relative to the counterfactual) 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 employment for firms with below median *ILM Access*. The median value of *ILM Access* 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. Table A29 reports the estimated coefficient, s.e., sample size.

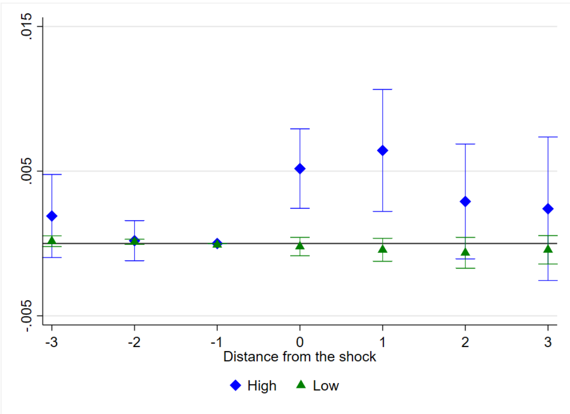
Figure A7: Impact of competitors' closures on shocked BG firms' market shares by ILM access – Sun & Abraham (2021)



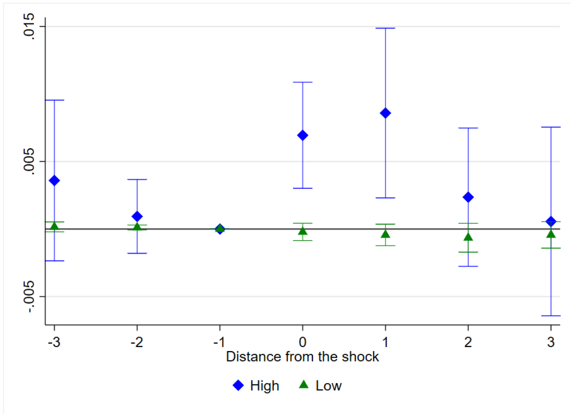
(a) ILM Access above median vs. below median



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



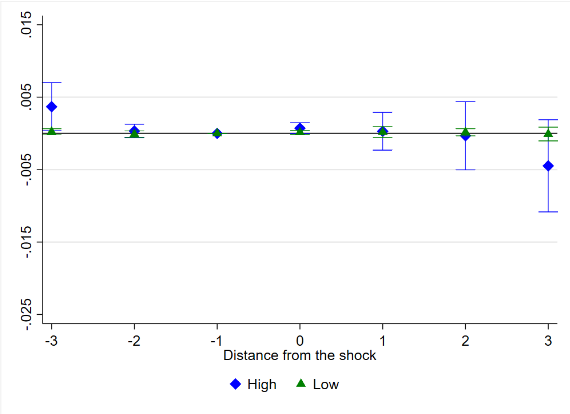
(c) ILM Access above median vs. below median



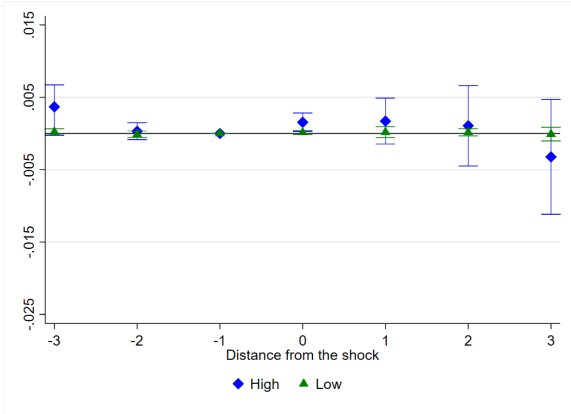
(d) ILM Access in top quartile vs. below median

Note: Panels (a)-(d) plots estimates for the dynamic effect of positive shocks on BG firms' market shares, depending on the level of *ILM Access*. We use Sun and Abraham (2021)'s IW estimator implemented using the STATA package **eventstudyinteract**. *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 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 shares from event date -1 to event dates $\tau \in [-3, +3]$ (relative to the counterfactual) 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 shares for firms with below median *ILM Access*. The median value of *ILM Access* 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. Table A30 reports the estimated coefficient, s.e., sample size.

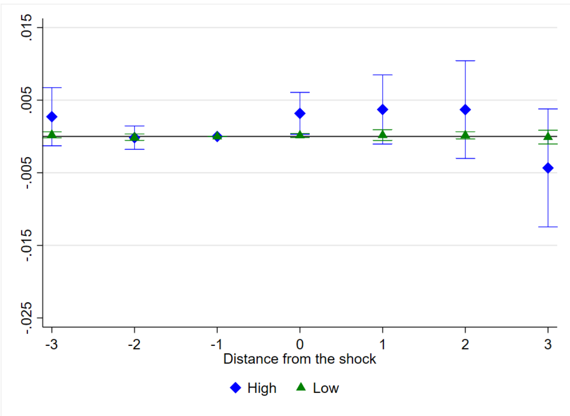
Figure A8: Impact of competitors' closures on shocked BG firms' market shares by ILM access – de Chaisemartin & D'Haultfœuille (2021)



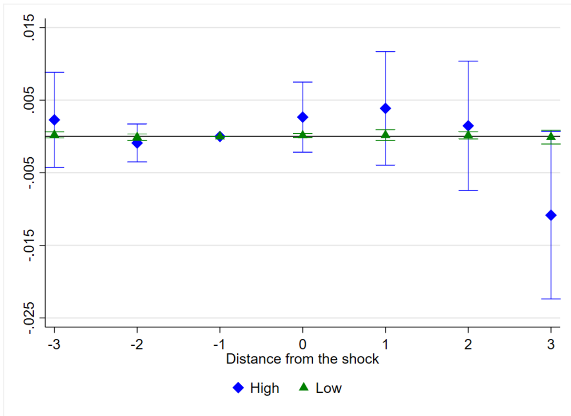
(a) ILM Access above median vs. below median



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



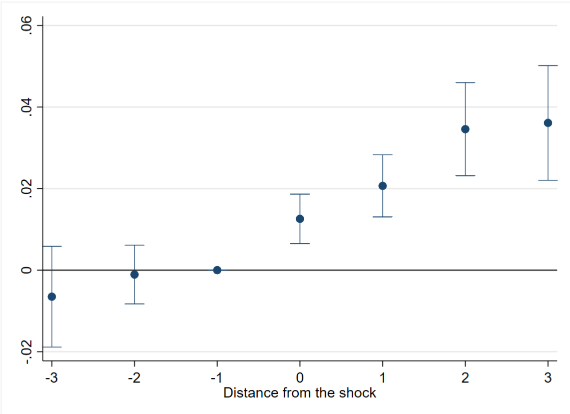
(c) ILM Access above median vs. below median



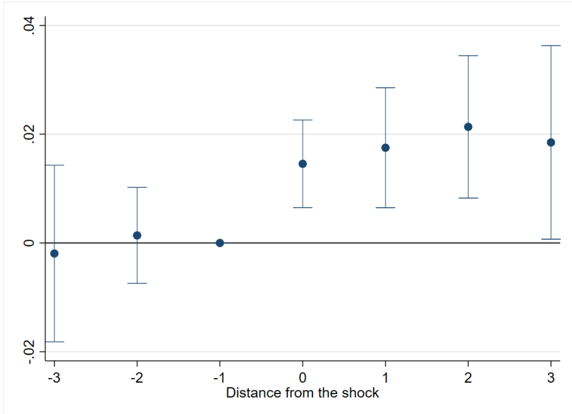
(d) ILM Access in top quartile vs. below median

Note: Panels (a)-(d) plots estimates for the dynamic effect of positive shocks on BG firms' market shares, depending on the level of *ILM Access*. We uses the estimator proposed by de Chaisemartin and D'Haultfœuille (2020) recently adapted to allow for dynamic effects (see de Chaisemartin and D'Haultfœuille (2021)). We implement this estimator using the STATA package `did_multiplegt`. *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 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 shares from event date -1 to event dates $\tau \in [-3, +3]$ (relative to the counterfactual) 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 shares for firms with below median *ILM Access*. The median value of *ILM Access* 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. Table A31 reports the estimated coefficient, s.e., sample size.

Figure A9: Impact of competitors' closures on worker flows from ILM partners



(a) Sun & Abraham (2021)



(b) de Chaisemartin & D'Haultfœuille (2021)

Note: Panel (a) plots estimates for the dynamic effect of positive shocks on bilateral worker flows from ILM partners using Sun and Abraham (2021)'s IW estimator implemented using the STATA package `eventstudyinteract`. Panels (b) uses instead the estimator proposed by de Chaisemartin and D'Haultfœuille (2020) recently adapted to allow for dynamic effects (see de Chaisemartin and D'Haultfœuille (2021)). We implement this estimator using the STATA package `did_multiplegt`. 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. 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 A26 reports the estimated coefficient, s.e., sample size.

A.5.1 Alternative DiD estimators: Tables

Table A26. Impact of competitors' closures on shocked BG firms' outcomes and bilateral ILM flows

Distance from the shock	Share of internal hires			Employment			Market shares			Internal bilateral flows		
	Sun & Abraham	dC & dH	N	Sun & Abraham	dC & dH	N	Sun & Abraham	dC & dH	N	Sun & Abraham	dC & dH	N
-3	-0.00071	0.00590	11,075	6.94625	-0.94504	6,002	0.00052	0.00185	6,002	-0.00650	-0.00194	6,393
	(0.00672)	(0.00524)		(4.47229)	(2.59309)		(0.00045)	(0.00128)		(0.00621)	(0.00829)	
-2	0.00577	-0.00651	15,832	1.83233	-1.14546	15,754	0.00019	0.00024	15,754	-0.00108	0.00139	21,508
	(0.00361)	(0.00414)		(1.95832)	(1.67049)		(0.00020)	(0.00034)		(0.00362)	(0.00450)	
-1	-	-	-	-	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-	-	-	-	-
0	0.00802	-0.00021	20,895	7.13339**	10.35142	21,829	0.00064*	0.00044*	21,829	0.01258***	0.01456***	29,296
	(0.00413)	(0.00503)		(2.64033)	(9.08616)		(0.00028)	(0.00021)		(0.00305)	(0.00411)	
1	0.01603**	0.01555**	12,963	10.28864*	19.08885	15,042	0.00087	0.00020	15,042	0.02066***	0.01752**	18,913
	(0.00524)	(0.00578)		(4.66641)	(14.95942)		(0.00047)	(0.00073)		(0.00383)	(0.00563)	
2	0.01932**	0.01231	8,510	0.90250	1.70184	9,548	0.00060	-0.00074	9,548	0.03457***	0.02135**	11,936
	(0.00726)	(0.00741)		(4.10398)	(4.82969)		(0.00069)	(0.00193)		(0.00574)	(0.00668)	
3	0.00862	0.00258	4,807	-4.58302	-11.09455	5,101	0.00083	-0.00200	5,101	0.03611***	0.01849*	6,372
	(0.00855)	(0.00966)		(4.85956)	(6.73377)		(0.00087)	(0.00233)		(0.00707)	(0.00908)	
N	34,318			37,173			37,173			45,794		

Note: The table reports estimates for the dynamic effect of positive shocks on BG firms' outcomes, using Sun and Abraham (2021)'s IW estimator implemented using the STATA package `eventstudyinteract`, and the estimator proposed by de Chaisemartin and D'Haultfœuille (2020) recently adapted to allow for dynamic effects (see de Chaisemartin and D'Haultfœuille (2021)). We implement this estimator using the STATA package `did_multiplegt`. Event date 0 is the year of the shock, i.e. the first year in which the large competitor is no longer active in a given industry. For the de Chaisemartin and D'Haultfœuille (2021) estimates, the table reports the number of observations used in the estimation of each coefficient: this number is the number of long differences of the outcome and of the treatment used in the estimation. *** denotes significance at the 0.1% level; ** denotes significance at the 1% level; * denotes significance at the 5% level.

Table A27. Impact of competitors' closures on shocked BG firms' Share of internal hires by ILM Access

	ILM Access			
	(1)	(2)	(3)	(4)
	Below Median	Above Median	Below Median	Above Median
Distance from the shock	Sun & Abraham		de Chaisemartin & D'Haultfœuille	
-3	-0.00694	0.00544	0.00348	0.01431
	(0.00709)	(0.00868)	(0.00618)	(0.00939)
	-	-	4,211	5,307
-2	0.00162	0.00979	-0.00289	-0.00892
	(0.00439)	(0.00527)	(0.00558)	(0.00734)
	-	-	6,311	7,814
-1	-	-	-	-
	-	-	-	-
	-	-	-	-
0	0.00169	0.01409*	0.00054	-0.00153
	(0.00398)	(0.00593)	(0.00428)	(0.00930)
	-	-	8,704	11,480
1	0.00387	0.02852***	0.00217	0.02873**
	(0.00593)	(0.00757)	(0.00608)	(0.01004)
	-	-	5,877	7,086
2	0.01339	0.02537*	0.00738	0.01740
	(0.00711)	(0.01099)	(0.00769)	(0.01298)
	-	-	3,841	4,669
3	0.00427	0.01279	-0.00282	0.00765
	(0.00869)	(0.01369)	(0.00948)	(0.01696)
	-	-	2,162	2,645
N	34,184		-	
Firm FE	YES		YES	

Note: The table reports estimates for the dynamic effect of positive shocks on on BG firms' *Share of internal hires*, depending on the level of *ILM Access*. We use Sun and Abraham (2021)'s IW estimator implemented using the STATA package `eventstudyinteract`, and the estimator proposed by de Chaisemartin and D'Haultfœuille (2020) recently adapted to allow for dynamic effects (see de Chaisemartin and D'Haultfœuille (2021)). We implement this estimator using the STATA package `did_multiplegt`. *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 j; (iii) in a different 4-digit industry than j. The median value of *ILM Acces* is equal to 1 worker. 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 *Share of internal hires* is the ratio of new hires that originate from same-group firms over total hiring of firm j. For the de de Chaisemartin and D'Haultfœuille (2021) estimates, we report the number of observations used in the estimation of each coefficient: this number is the number of long differences of the outcome and of the treatment used in the estimation. *** denotes significance at the 0.1% level; ** denotes significance at the 1% level; * denotes significance at the 5% level.

Table A28. Impact of competitors' closures on shocked BG firms' employment by ILM access (Sun & Abraham, 2021)

	ILM Access							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Distance from the shock	Above Median	Below Median	Top Quartile	Below Median	Top Decile	Below Median	95th percentile	Below Median
-3	13.30334	3.08345	15.70781	2.25387	30.48147	2.25387	72.03046	2.25387
	(8.17123)	(2.35662)	(15.48869)	(2.42439)	(39.74634)	(2.42515)	(83.87665)	(2.42550)
-2	3.38490	1.17393	1.69071	0.93759	1.22329	0.93759	24.29436	0.93759
	(3.19394)	(1.48167)	(5.75256)	(1.55342)	(13.77468)	(1.55391)	(28.04218)	(1.55413)
-1	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-
0	11.29425*	2.31558	25.43251**	-0.23231	59.48433**	-0.23231	57.77628*	-0.23231
	(4.67557)	(1.48941)	(8.71769)	(2.81197)	(20.76672)	(2.81285)	(27.75023)	(2.81325)
1	20.37892*	-0.45640	45.28462**	-3.95045	97.53578**	-3.95045	96.38177	-3.95045
	(8.50498)	(1.66969)	(15.40133)	(3.56399)	(34.16489)	(3.56511)	(49.33466)	(3.56562)
2	4.18066	-5.11136*	15.49314	-9.48507*	32.30326	-9.48507*	-2.49050	-9.48507*
	(8.94847)	(2.23156)	(14.46829)	(4.68272)	(31.35233)	(4.68419)	(41.16287)	(4.68486)
3	4.84882	-8.30236***	0.21469	-13.41321*	-0.28558	-13.41321*	-64.87794	-13.41321*
	(11.83492)	(2.12255)	(19.18961)	(5.61642)	(41.47573)	(5.61819)	(56.46722)	(5.61898)
N	37,173		28,580		23,219		21,403	
Firm FE	YES		YES		YES		YES	

Note: The table reports estimates for the dynamic effect of positive shocks on BG firms' employment, depending on the level of *ILM Access*. We use Sun and Abraham (2021)'s IW estimator implemented using the STATA package `eventstudyinteract`. *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 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 median value of *ILM Access* 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. *** denotes significance at the 0.1% level; ** denotes significance at the 1% level; * denotes significance at the 5% level.

Table A29. Impact of competitors' closures on shocked BG firms' employment by ILM access (de Chaisemartin & D'Haultfœuille, 2021)

	ILM Access							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Distance from the shock	Above Median	Below Median	Top Quartile	Below Median	Top Decile	Below Median	95th percentile	Below Median
-3	-2.05485	0.83790	-10.37747	0.83790	-26.55907	0.83790	-50.93519	0.83790
	(5.54490)	(3.51819)	(6.86274)	(3.51819)	(19.09285)	(3.51819)	(31.01376)	(3.51819)
	2,919	3,083	1,300	3,083	465	3,083	225	3,083
-2	-1.02397	-0.56329	-3.75738	-0.56329	-10.89550	-0.56329	-6.47633	-0.56329
	(2.13852)	(3.90532)	(4.54116)	(3.90532)	(11.62925)	(3.90532)	(22.32136)	(3.90532)
	7,657	8,097	3,512	8,097	1,294	8,097	617	8,097
-1	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-
0	6.60149	23.56146	15.99185*	23.56146	39.75406	23.56146	25.42796	23.56146
	(3.89078)	(27.14705)	(8.04116)	(27.14705)	(21.33603)	(27.14705)	(32.99848)	(27.14705)
	10,699	11,130	4,977	11,130	1,866	11,130	894	11,130
1	13.86194*	28.04356	32.92196*	28.04356	78.29826*	28.04356	71.35758	28.04356
	(5.90219)	(33.10447)	(12.85295)	(33.10447)	(32.56006)	(33.10447)	(51.38853)	(33.10447)
	7,387	7,655	3,369	7,655	1,254	7,655	606	7,655
2	8.85430	-7.22799**	25.44715	-7.22799**	63.25708	-7.22799**	18.59351	-7.22799**
	(9.39171)	(2.38234)	(20.04786)	(2.38234)	(49.40179)	(2.38234)	(78.14739)	(2.38234)
	4,628	4,920	2,140	4,920	806	4,920	394	4,920
3	-12.68317	14.70925***	-12.32815	14.70925***	-20.54813	14.70925***	-1.33e+02	14.70925***
	(14.00836)	(3.28866)	(25.53897)	(3.28866)	(60.35049)	(3.28866)	(95.35163)	(3.28866)
	2,481	2,620	1,198	2,620	462	2,620	227	2,620
Firm FE	YES		YES		YES		YES	

Note: The table reports estimates for the dynamic effect of positive shocks on BG firms' employment, depending on the level of *ILM Access*. We uses the estimator proposed by de Chaisemartin and D'Haultfœuille (2020) recently adapted to allow for dynamic effects (see de Chaisemartin and D'Haultfœuille (2021)). We implement this estimator using the STATA package `did_multiplegt`. *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 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 median value of *ILM Access* 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 report the number of observations used in the estimation of each coefficient: this number is the number of long differences of the outcome and of the treatment used in the estimation. *** denotes significance at the 0.1% level; ** denotes significance at the 1% level; * denotes significance at the 5% level

Table A30. Impact of competitors' closures on shocked BG firms' market shares by ILM access (Sun & Abraham, 2021)

	ILM Access							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Distance from the shock	Above Median	Below Median	Top Quartile	Below Median	Top Decile	Below Median	95th percentile	Below Median
-3	0.00107*	0.00018	0.00147	0.00016	0.00190	0.00016	0.00359	0.00016
	(0.00052)	(0.00021)	(0.00092)	(0.00019)	(0.00147)	(0.00019)	(0.00303)	(0.00019)
-2	0.00031	0.00012	0.00033	0.00012	0.00019	0.00012	0.00093	0.00012
	(0.00023)	(0.00010)	(0.00040)	(0.00009)	(0.00071)	(0.00009)	(0.00139)	(0.00009)
-1	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-
0	0.00136***	-0.00009	0.00263***	-0.00021	0.00518***	-0.00021	0.00694***	-0.00021
	(0.00036)	(0.00029)	(0.00066)	(0.00033)	(0.00140)	(0.00033)	(0.00200)	(0.00033)
1	0.00195**	-0.00025	0.00374**	-0.00044	0.00643**	-0.00044	0.00859**	-0.00044
	(0.00066)	(0.00036)	(0.00120)	(0.00041)	(0.00215)	(0.00041)	(0.00320)	(0.00041)
2	0.00146	-0.00043	0.00262	-0.00065	0.00290	-0.00065	0.00236	-0.00065
	(0.00091)	(0.00049)	(0.00157)	(0.00054)	(0.00202)	(0.00054)	(0.00261)	(0.00054)
3	0.00164	-0.00021	0.00301	-0.00043	0.00240	-0.00043	0.00056	-0.00043
	(0.00118)	(0.00043)	(0.00201)	(0.00050)	(0.00253)	(0.00050)	(0.00356)	(0.00050)
N	37,173		28,580		23,219		21,403	
Firm FE	YES		YES		YES		YES	

Note: The table reports estimates for the dynamic effect of positive shocks on BG firms' market shares, depending on the level of *ILM Access*. We use Sun and Abraham (2021)'s IW estimator implemented using the STATA package `eventstudyinteract`. *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 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 median value of *ILM Access* 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. *** denotes significance at the 0.1% level; ** denotes significance at the 1% level; * denotes significance at the 5% level.

Table A31. Impact of competitors' closures on shocked BG firms' market shares by ILM access (de Chaisemartin & D'Haultfœuille, 2021)

	ILM Access							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Distance from the shock	Above Median	Below Median	Top Quartile	Below Median	Top Decile	Below Median	95th percentile	Below Median
-3	0.00368*	0.00023	0.00368*	0.00023	0.00272	0.00023	0.00229	0.00023
	(0.00169)	(0.00022)	(0.00178)	(0.00022)	(0.00205)	(0.00022)	(0.00334)	(0.00022)
	2,919	3,083	1,300	3,083	465	3,083	225	3,083
-2	0.00033	-0.00010	0.00031	-0.00010	-0.00016	-0.00010	-0.00089	-0.00010
	(0.00048)	(0.00023)	(0.00059)	(0.00023)	(0.00082)	(0.00023)	(0.00133)	(0.00023)
	7,657	8,097	3,512	8,097	1,294	8,097	617	8,097
-1	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	-
0	0.00072	0.00014	0.00155*	0.00014	0.00318*	0.00014	0.00266	0.00014
	(0.00038)	(0.00014)	(0.00065)	(0.00014)	(0.00147)	(0.00014)	(0.00246)	(0.00014)
	10,699	11,130	4,977	11,130	1,866	11,130	894	11,130
1	0.00030	0.00018	0.00171	0.00018	0.00372	0.00018	0.00387	0.00018
	(0.00133)	(0.00038)	(0.00162)	(0.00038)	(0.00243)	(0.00038)	(0.00399)	(0.00038)
	7,387	7,655	3,369	7,655	1,254	7,655	606	7,655
2	-0.00033	0.00016	0.00107	0.00016	0.00370	0.00016	0.00147	0.00016
	(0.00240)	(0.00025)	(0.00284)	(0.00025)	(0.00343)	(0.00025)	(0.00454)	(0.00025)
	4,628	4,920	2,140	4,920	806	4,920	394	4,920
3	-0.00448	-0.00009	-0.00323	-0.00009	-0.00433	-0.00009	-0.01084	-0.00009
	(0.00325)	(0.00048)	(0.00404)	(0.00048)	(0.00415)	(0.00048)	(0.00589)	(0.00048)
	2,481	2,620	1,198	2,620	462	2,620	227	2,620
Firm FE	YES		YES		YES		YES	

Note: The table reports estimates for the dynamic effect of positive shocks on BG firms' market shares, depending on the level of *ILM Access*. We uses the estimator proposed by de Chaisemartin and D'Haultfœuille (2020) recently adapted to allow for dynamic effects (see de Chaisemartin and D'Haultfœuille (2021)). We implement this estimator using the STATA package `did_multiplegt`. *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 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 median value of *ILM Access* 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 report the number of observations used in the estimation of each coefficient: this number is the number of long differences of the outcome and of the treatment used in the estimation. *** denotes significance at the 0.1% level; ** denotes significance at the 1% level; * denotes significance at the 5% level.