The Internal Labor Markets of Business Groups *

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Abstract

This paper provides micro evidence of labor mobility inside business groups. We show that worker flows between firms in the same group are stronger than with unaffiliated firms. Moreover, the reallocation of top workers between group firms is more sensitive to international shocks. Top workers that move within the group in response to shocks reach higher positions and earn higher wages. We find suggestive evidence that productivity increases when firms receive same-group top workers. Our results are consistent with the hypothesis that, in response to changing opportunities, joint ownership eases the redeployment of workers endowed with general management skills.

Keywords: Internal labor markets; business groups; labor reallocation; trade shocks.

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1 Introduction

Business groups are common corporate structures around the world. More than half of all listed firms in emerging markets, and a sizable fraction in many developed countries, are affiliated to business groups (Khanna and Yafeh 2007; Morck, Wolfenzon, and Yeung 2005). Business groups consist of legally independent firms controlled by the same ultimate shareholder. As an example, Figure 1 shows the corporate structure of Antarchile, one of the largest business groups in Chile and controlled by the Angelini family. There are several reasons that can explain the existence of these complex ownership structures. One explanation argues that business groups create factor markets between affiliated firms to alleviate frictions in external markets. Along these lines, there is growing evidence that business groups transfer capital between firms to overcome financial constraints.[1]

Little is known about other factor markets in business groups. Internal labor markets, in particular, can allow business groups to overcome frictions in external labor markets. Reallocating workers through the internal market can be cheaper and more effective than through the external market. In this paper, we provide evidence that business groups actively use internal labor markets. We find that, in response to international shocks, there is more labor reallocation between firms in the same group than with unaffiliated firms, and in particular for the case of top workers. We also find suggestive evidence that internal labor flows increase productivity at the firm level, which is consistent with the idea that internal labor markets can give group firms an advantage over standalone firms. Overall, we identify a new advantage of business groups.

We study the internal labor markets of business groups with novel micro data for the Chilean economy between 2004 and 2015. We have access to a matched employer-employee dataset for all workers in the private sector. Our data allows us to follow workers as they switch jobs, thus, our unit of analysis is a pair of firms with a positive worker flow in a given

[1] See Gopalan, Nanda, and Seru (2007), Boutin, Cestone, Fumagalli, Pica, and Serrano-Velarde (2013), Buchuk, Larrain, Munoz, and Urzúa (2014), Almeida, Kim, and Kim (2015), and Buchuk, Larrain, Prem, and Urzúa (2020).

moment in time. We merge the employment data with hand-collected firm ownership data in order to determine which firms belong to business groups, and which firms are standalone firms. We study labor reallocation between firms in response to international firm-level price shocks, in the style of Autor, Dorn, and Hanson (2013), and Hummels, Jørgensen, Munch, and Xiang (2014). This strategy takes advantage of Chile's position in the world economy as an exporter of natural resources (e.g., copper, wood pulp, fruit, wine, salmon, nitrate). Shocks to the international prices of these commodities are exogenous to the labor flows that we want to explain and to other firm characteristics (e.g., being affiliated to a group).

Imagine that a group firm receives a negative shock to the prices of its exports, and therefore reduces its demand for labor. Neoclassical theory suggests that this firm should redeploy workers towards other firms with better prospects, regardless of whether those firms belong to the same business group or not. Instead, we find that more workers are redeployed towards affiliated firms rather than to unaffiliated firms. This result is in line with the evidence of labor reallocation in U.S. conglomerates (Tate and Yang, 2015). Our results are stronger for the case of top workers, which we define as those in the top quartile of the within-firm wage distribution. Based on our estimates, we find that there is 20% more reallocation of top workers towards same-group firms than to unaffiliated firms in response to export shocks. This effect controls for the size and wage levels of the firms of origin and destination of the worker, as well as for other firm characteristics and fixed effects.

Top workers that move between group firms in response to export shocks see their wages increase by close to 7%. This wage increase can reflect rent-sharing or a positive pass-through of shocks towards employees (e.g., Kline, Petkova, Williams, and Zidar 2019; Friedrich, Laun, Meghir, and Pistaferri 2019). It is also broadly consistent with the findings of Tate and Yang (2015) who report that top workers gain the most (relative to other workers) by moving within diversified conglomerates. In our sample, workers who move to unaffiliated firms experience wage losses on average. We do not have data on job categories, but we proxy for promotions using the change in within-firm wage ranking of the worker that moves. We find that top workers who are transferred within the group in response to export shocks move to higher positions, i.e., they climb the corporate ladder.

After documenting the extent of labor reallocation inside business groups, we explore its potential drivers. A first thing to note is that financial constraints, which are a standard explanation for the existence of internal *capital* markets (Hoshi, Kashyap, and Scharfstein 1991), do not necessarily imply the existence of internal *labor* markets. While the flow of internal capital towards a firm can go hand in hand with more employment (Giroud and Mueller 2015), this increase in employment can be done by hiring from the external labor market. In order to explain a preference for same-group workers we need to study frictions that make the redeployment of internal workers more convenient than hiring external workers. In other words, these frictions must break the perfect substitutability that in principle exists between internal and external workers.

We do not find evidence in support of some frictions explored in the previous literature, namely, transaction costs (e.g., severance payments, training costs), and unemployment insurance. For instance, the wage pass-through that we find is inconsistent with perfect insurance provided by the business group to its workers. Admittedly, we only employ rough proxies for these frictions, so we cannot fully rule out any of them.

We also explore skill differentials between internal and external workers. Some skills may only be acquired internally, or they may be hard to verify in external workers because of asymmetric information. We do not find that worker tenure is related to stronger reallocation within the group, which speaks against job-specific skills. Similarly, sector integration between the firms of origin and destination does not affect reallocation, which speaks against the relevance of skills correlated with the industrial process. Our results are most consistent with the importance of general management skills as drivers of internal labor mobility. General skills are particularly relevant for top workers (Frydman 2020; Kaplan, Klebanov, and Sorensen 2012). General skills are also more easily transferred across firms with a common organizational culture. For example, we find that reallocation is stronger when the firm of origin controls the firm of destination of the top worker.

Finally, we study whether the arrival of a top worker from within the business group creates value in the destination firm. If the new worker is endowed with more skills, and if she is in a top position, she can potentially have an impact on the entire firm. As shown by Bloom, Eifert, Mahajan, McKenzie, and Roberts (2013), better managerial practices can have large effects on firm-level productivity. The analysis of productivity in response to internal labor mobility can also help explain productivity differentials when comparing affiliated and unaffiliated firms (e.g., Schoar 2002). Using the synthetic control approach of Abadie and Gardeazabal (2003), and Abadie, Diamond, and Hainmueller (2010), we find that firms that receive a top worker from within the group increase net exports over their wage will, net exports per employee, and average wages. Hence, our results suggest that internal labor mobility adds value by reallocating top workers across group firms. Because most firms in our sample are private firms, we do not have the data required to compute more direct measures of productivity, such as profits or total factor productivity (TFP). Partly for this reason, we view this evidence only as suggestive.

Although ownership structures move at a lower frequency than shocks, and hence it is hard to argue that they are endogenous to particular shocks, it is also true that group affiliation does not occur randomly. Group affiliation may be simultaneously determined with other variables that also influence reallocation. For example, firms that are geographically closer or that operate in sectors that are industrially integrated can end up affiliated to the same business group. Because of those underlying forces, affiliated firms may experience more labor reallocation between them. We address the omitted variables problem by adding interactions of shocks with other characteristics at the firm-pair level, such as geographical distance and industrial integration. Our results show that group affiliation matters for between-firm reallocation above and beyond these other reallocation channels that we can observe and control for. However, we cannot fully rule out that some unobservable variable drives both group affiliation and the response of labor flows to shocks.

Despite the endogeneity caveat, our results still allow us to learn if affiliated firms behave differently from other firms with similar characteristics, or that experience similar shocks. Theory suggests that joint ownership can have positive or negative effects on the allocation of resources (Grossman and Hart 1986; Stein 1997; Scharfstein and Stein 2000; Duchin and Sosyura 2013). Hence, regardless of the motives that might drive affiliation, it is worth studying if, once affiliated, firms show a stronger or weaker response to shocks. This evidence can give us hints regarding which effect dominates. Our results provide a first step towards an answer within the novel setup of labor reallocation in business groups.

Our results contribute, first and foremost, to the literature on business groups (Khanna and Yafeh 2007). The internal labor markets of business groups are less studied than internal capital markets, but are potentially equally important to understand the rationale behind the formation of business groups. Our paper, together with Belenzon and Tsolmon (2016), Faccio and O'Brien (2017), and Cestone, Fumagalli, Kramarz, and Pica (2018), belongs to the nascent study of the internal labor markets of business groups. The first two papers use firm-level data in a cross-country setting. Our paper is closest to Cestone, Fumagalli, Kramarz, and Pica (2018), who also use employer-employee matched data.

The incremental contribution of our paper with respect to Cestone, Fumagalli, Kramarz, and Pica (2018) is threefold. First, the shocks that we study are different. Cestone, Fumagalli, Kramarz, and Pica (2018) study the closure of large competitors, and mass layoffs or plant closures in France. Our shocks are derived from international prices, which are exogenous with respect to labor flows between origin and destination firms, and are relevant proxies for changing business conditions in small and open economies. Second, our results on wage dynamics are different. In Cestone, Fumagalli, Kramarz, and Pica (2018), workers experience wage decreases in response to closures as they move within the group (with little difference across occupational categories), while we find that top workers experience wage increases in response to shocks as they move within the group. The fact that bottom workers are less likely to transition to unemployment leads Cestone, Fumagalli, Kramarz, and Pica

(2018) to argue in favor of the insurance hypothesis. Our results throughout the paper are focused on top workers rather than bottom workers. Both our and their results are likely to be complementary rather than contradictory, given the different nature of the shocks that the two papers study. We also complement the study of wage changes with changes in wage-rankings as proxy for movements in the corporate hierarchy. Finally, we study the effects of top labor flows on destination firms. Cestone, Fumagalli, Kramarz, and Pica (2018) study firm-level outcomes in relation to general group affiliation or broad measures of access to internal labor markets, but not in relationship to the arrival of particular workers from within the group.

Our paper also contributes to the broader literature on the internal labor markets of conglomerates (Giroud and Mueller 2015; Tate and Yang 2015; Tate and Yang 2019; Silva 2020). Although similar mechanisms apply to both conglomerates and business groups, a key difference is that worker flows are *within* a firm in conglomerates and *between* firms in business groups. Different divisions or plants in a conglomerate share a common balance sheet, they typically have integrated human resources departments, distribution channels, and so on. Such integration blurs firm boundaries. In business groups the controlling shareholder is often the only link between firms that are, otherwise, independent corporations. Both ownership structures provide significant control rights, but without erasing firm boundaries in the case of business groups. This subtle difference can have an impact on the nature of internal labor markets. In particular, our results suggest that the internal labor markets of business groups alleviate market frictions for top workers, while the previous literature on conglomerates and multi-plant firms finds effects across all types of workers. From the point of view of control rights (Hart 2001), our results emphasize that exercising control often means reallocating top workers. Our results suggest that control is valuable, at least in part, because it allows for a swift redeployment of top workers in response to changes in market conditions.

Finally, our results speak to the literature on labor reallocation in response to shocks, in particular international shocks (Autor, Dorn, and Hanson 2013; Hummels, Jørgensen, Munch, and Xiang 2014). We add to this literature a focus on ownership networks as an important element of the transmission mechanism. Our results are in line with Atalay, Hortaçsu, and Syverson (2014), who argue that joint ownership helps in the reallocation of intangible inputs (see also Ding, Fort, Redding, and Schott 2019). Since intangible inputs are often embedded in top workers, transferring intangibles means reallocating top workers. More broadly, our results contribute to the evidence on networks as transmission mechanism for shocks. Production networks based on input-output linkages (Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi 2012), and financial networks (Elliott, Golub, and Jackson 2014) can propagate shocks. Our results show that ownership networks can also propagate shocks by inducing labor reallocation between firms.

The remainder of the paper proceeds as follows. Section 2 describes the different data sets that we combine in our paper. Section 3 presents the main evidence in support of internal labor markets. Section 4 tests for different rationales behind internal labor mobility. Section 5 discusses the firm-level effects of internal labor markets. Section 6 concludes. The Appendix provides supplementary data description and results.

2 Data Sources and Summary Statistics

We combine three datasets to study the internal labor markets of business groups. First, we use a matched employer-employee dataset to identify worker flows between firms. Second, we use an ownership dataset to link the firms in our sample. Third, we construct a firm-level measure of shocks to business conditions using customs data with export and import quantities and prices.[2]

[2] Appendix A.1 describes in detail the cleaning and merging procedures that we use, and some limitations of the three datasets.

2.1 Matched Employer-Employee Data

Chilean firms are required by law to pay a fraction of workers' monthly wages into an individual savings account, and a common fund that can be used by all workers in case of unemployment. The unemployment insurance system is managed by a private entity that keeps the Unemployment Insurance dataset. We obtained access to this data for the period between 2004 and 2015. This dataset provides wage information for each employer-employee relationship. Firms also report their main industry, and the gender and birth date of each worker. The dataset does not report information of the professional category or occupation of the worker. Past research on employer-employee matching has used similar datasets from other countries, such as Germany and Portugal (Card, Heining, and Kline, 2013).

This dataset has three features that are relevant for our study. First, it covers the entire (formal) private labor market in Chile. Second, because Chile's administrative datasets have unique tax IDs for both workers and firms, we can keep track of both of them across time and merge this dataset with other datasets. The unemployment dataset includes listed and private firms. We use the listed firms to merge the employment data with ownwership data. Finally, given that we have the employer-employee relationships, we have the entire wage distribution within and across firms.

2.2 Ownership Data

We classify firms into business-group firms and standalone firms. Chilean listed firms are required by law to report financial statements and ownership structures to the local stock market regulator (Financial Markets Commission). From the universe of listed firms, we define a business group as a set of two or more firms with a common controlling shareholder (Buchuk, Larrain, Munoz, and Urzúa 2014). Financial statements typically report links between corporations, but not the names of the ultimate shareholder. We identify the controlling shareholder by checking the composition of boards, annual reports, and the financial press. Controlling shareholders are families, foreign multinationals, or small groups of large investors who act in a coordinated way. The state is not a relevant controlling shareholder of listed firms in Chile. The ownership structures of business groups are stable across across long periods of time in the Chilean market (Donelli, Larrain, and Urzúa 2013). The birth of most business groups in our sample was forged in the economic liberalization of the late 1970s and early 1980s (Larrain and Urzúa 2016).

Using the information reported by the listed firms we can track the private firms that are related to the listed firms, and hence that also belong to business groups. Ownership links with private firms are reported in two ways. First, there is a list of firms that consolidate with a listed firm. Accounting consolidation means that the firm exerts a controlling influence over the other firm. In practice, consolidation typically implies an ownership stake above 50%. Second, there is a list of related investments made by a listed firm. These are firms where the listed firm has a large and permanent investment, although the type of influence does not imply accounting consolidation. Related investments typically involve ownership stakes between 10% and 50%. Because ownership stakes are significant we consider that the firms in related investments also belong to a group if their parent has been identified as a group firm.

Using all the previous information we define the set of firms –listed and private– that conform each business group. Firms that are not in a business group are classified as standalone firms. During our sample period, 2004-2015, we identify 29 business groups covering 93 listed firms and multiple private firms. Figure 1 provides an example of a business group in our data. The group is controlled by the Angelini family and has five listed firms: the holding company –Antarchile– at the top of the pyramid, plus four firms in the second layer of the ownership structure. These firms operate in diverse industries such as fishing, wood pulp, oil and gas, electricity, and others.

2.3 International Trade Data

The previous literature on internal labor markets uses changes in Tobin's Q to proxy for business conditions (e.g., Tate and Yang 2015). This poses a challenge in our setup because our sample has a majority of private firms. Two other factors work against using the local stock market as measure of shocks in our case. First, the local stock market is highly concentrated. For example, the main stock index (IPSA) covers only 30 companies, while other stocks are sparsely traded. Second, the local stock market does not have a broad coverage of industries. For instance, mining is barely present despite the importance of this industry for Chile's GDP.

Instead of Tobin's Q we measure business conditions with international trade data.[3] Chile is a big exporter of natural resources (e.g., copper, fruit, wine, salmon, nitrate, wood pulp, etc.). Our approach takes advantage of Chile's small and open economy. The downside is that our shocks apply only to firms that are exposed to international trade. For example, firms that engage in international trade are typically larger than other firms in the economy (Melitz, 2003; Bernard, Eaton, Jensen, and Kortum, 2003).

Our measure of business conditions consists of *firm*-level export and import shocks in the style of Autor, Dorn, and Hanson (2013), and Hummels, Jørgensen, Munch, and Xiang (2014). We use two sources of trade data to construct these shocks. First, customs data provide detailed import and export activity for Chilean firms at the annual frequency. Each firm reports the quantity and value of every international transaction with information at the product-country level combination. Product definition is at the six-digit level from the Harmonized System. Second, we use trade data at the product-country level coming from a repository of official trade information collected by the UN Statistical Division, Comtrade. We build international prices for every product-country combination from these data. Following the trade literature, we ignore trade flows with Chile when computing international

[3] In Appendix A.2 we show that our main results are robust to using shocks to Tobin's Q at the industry level.

prices. We could, in principle, compute prices for exports and imports in each firm with the previous customs data. However, and although Chilean firms are small relative to global markets, some of the variation in these prices could be endogenous to the specific characteristics of the local firms (e.g., being affiliated to a business group). For our particular setup, these prices could be endogenous to the labor flows that we are trying to explain.

We define export shock x for firm i in year t with a Bartik-type strategy (Bartik 1991; Blanchard and Katz 1992):

$$\Delta\text{Price}_{it}^{x} = \sum_{j} s_{ij0} \Delta\text{Price}_{jt}^{Gx}$$

Price_{jt}^{Gx} is the log global price of product-country combination j being exported in year t, and s_{ij0} is the share of this product-country combination relative to all the exports of firm i in the initial year (2004). Import shocks are defined analogously. A increase in export prices represents a positive shock for an exporting firm, while an increase in import prices represents a negative shock for an importing firm.

Because most trade flows are concentrated in firms that simultaneously export and import, we assess the relative importance of each activity for the firms in our sample. First, we compare exports and imports to each firm's wage bill. We find that, on average, for every dollar spent in wages firms spend \$1.3 in imports and receive \$2 in exports. Second, we explore the different nature of export and import shocks. As seen in Appendix Table A.1, export prices for Chilean firms are more volatile than import prices. Average price changes are also higher for exports than for imports in this sample. These differences hold for standalone and group firms alike. Overall, these results suggest that export shocks are more relevant than import shocks in our sample.

Appendix Table A.2 shows that both group firms and standalone firms with exposure to international trade represent a significant fraction of the universe of firms in each category. It shows that 43% of group firms engage in exports and 68% of them in imports. Stand-alone firms that export and import correspond, respectively, to 14% and 33% of all standalone firms. Since firms that engage in international trade are larger (Melitz, 2003; Bernard, Eaton, Jensen, and Kortum, 2003), the exposure measures are higher when considering the fraction of employment and wage bills exposed to trade (columns 2 and 3 of Appendix Table A.2). Conservatively speaking, at least a quarter of employment and a third of the wage bill are exposed to international trade.[4]

2.4 Summary Statistics

Table 1 reports summary statistics for our merged employment-ownership-trade sample. We have on average 66,001 firms per year, of which 236 are business-group firms and 65,765 are standalone firms. We have data on roughly 3.3 million workers per year, of which 103,308 work in business-group firms and the rest work in standalone firms. Group firms are larger than stand-alone firms: the average group firm has 438 workers on its payroll, while the average standalone firm has only 49 workers.

Our main unit of analysis is the bilateral flow of workers between two firms. For each pair of firms we compute the number of workers moving from an origin firm to a destination firm every year. As in Cestone, Fumagalli, Kramarz, and Pica (2018), we focus on firm pairs in which the origin firm belongs to a business group. Table 1 shows that there are 22,789 unique firm-pairs where the origin firm is a group firm. Some of these pairs have repeated flows during the sample. Out of the 2,475 unique pairs in the average year, there are 160 pairs where both the origin and destination firms belong to the same business group; the remaining 2,315 firm pairs have a group firm as origin and an unaffiliated firm (in another business group or a standalone firm) as destination.

Table 2 reports summary statistics for worker flows. We define the worker flow as the number of workers moving from the origin firm to the destination firm, relative to the total

[4]Relative to the employment dataset, the trade dataset is less intensive in services and more intensive in manufacturing. Despite the overall importance of copper mining in Chile, this industry represents less than 5% of our employment data. This industry is relatively more capital-intensive. Moreover, many of the large mining firms are state-owned, and hence are not part of the private employment dataset.

number of workers that leave the origin firm for other firms that year.[5] Out of 100 workers a group firms sends to other firms in a given year, 5.3 workers are sent to the average firm in the same group, while 1.9 workers are sent to the average unaffiliated firm.[6] The strength of same-group flows can be seen across segments of the within-firm wage distribution. Top workers are defined as the workers in the top quartile of the origin firm's wage distribution. We do not find similar results when defining top workers from the overall wage distribution in the economy, which suggests that our findings are about top positions within a firm, rather than about high nominal wages.

Table 2 also reports summary statistics for wage changes. When a worker moves to another firm in the same business group, her wage increases by 5.1%; while if she moves to an unaffiliated firm, her wage decreases by 3.2%. This is similar to the findings of Tate and Yang (2015) for workers that move within conglomerates and those who leave. Interestingly, the spread in wage changes between workers that move within a group and those who move to unaffiliated firms is largest among top-workers. These calculations only include changes that are not top-coded. In our sample, the share of top worker flows with top-coded wages is 11.6%, which only introduces a downward bias in wage increases.

[5] We refer to these as labor outflows. We also present labor inflows, where we set all destination firms to be group firms, whereas origin firms can be either group firms or stand-alone firms. In this case we normalize the worker flow by the total number of workers absorbed by the destination firm. In Appendix Table A.3 we show average inflows and outflows side by side, so it is easy to see that the effects are similar. The literature is in general focused on outflows following mass layoffs and plant closures to ameliorate selection issues (Jacobson, LaLonde, and Sullivan 1993; Davis and von Wachter 2011).

[6] Appendix Table A.3 shows the strong statistical significance of these differences. Average worker flows between affiliated and unaffiliated firms do not add up to 100% because these numbers are defined at the firm-pair level. In order for them to sum up to 100%, they need to be scaled up by how many relationships a given firm has on each margin.

3 Tests of Internal Labor Markets

3.1 Empirical Design

We study worker flows between a destination firm d and an origin group-firm o in year t. Our baseline regression specification is as follows:

$$\begin{aligned} \text{Worker Flow}_{dot} = & \ \beta \text{Same Business Group}_{do} + \gamma \Delta \text{Export Price}_{dot} \\ & + \delta [\text{Same Business Group}_{do} \times \Delta \text{Export Price}_{dot}] \\ & + \lambda' \text{X}_{dot} + \alpha_d + \alpha_o + \alpha_t + \epsilon_{dot}. \end{aligned} \tag{3.1}$$

The dummy variable Same Business Group$_{do}$ takes the value of one if the destination and origin firms belong to the same business group, and zero otherwise. Group affiliation is defined at the beginning of the sample to ensure that it precedes worker flows. The variable ΔExport Price$_{dot}$ is the relative export shock between the destination firm and the origin firm, i.e., $\Delta\text{Export Price}_{dot} = \Delta\text{Price}^x_{dt} - \Delta\text{Price}^x_{ot}$. We normalize the relative shock by its standard deviation, such that the coefficient γ represents the effect of a one-standard-deviation increase in the relative shock. Import shocks are defined analogously. Equation (3.1) uses gross worker flows, and therefore firm pairs with flows to and from each other in the same year are two different observations. The regression with gross flows instead of net flows represents a stricter test because relative shocks imply worker reallocation in only one direction.[7]

Besides the interaction between the same-group dummy and the price shocks, we add a vector of destination and origin firm controls (X_{dot}), which includes average firm wages, firm size (number of employees), and business group characteristics (e.g., number of firms in the group). Destination firm (α_d) and origin firm (α_o) fixed effects control for all time-invariant firm characteristics; and year fixed effects (α_t) account for annual shocks that are common

[7] Firm pairs with flows in both directions represent 12.1% of the observations. The results with net flows are analogous to the results with gross flows.

to all firms. It would be ideal to include pair fixed effects, but unfortunately we do not have enough repeated flows between pairs of firms to do this.[8] We double cluster the standard errors at both the origin-firm and destination-firm levels.[9]

The coefficient β captures the average or unconditional worker flow between two firms in the same group. Under the neoclassical theory $\beta = 0$, because the fact that two firms are related through a common owner should not matter for worker reallocation. This can be understood as the labor-market version of the irrelevance proposition of Modigliani and Miller (1958). If, instead, business groups use internal labor markets, then we should find a positive and statistically significant β.

The coefficient δ on the interaction between the same-group dummy and the shocks captures the excess sensitivity of same-group worker flows to international shocks. The null hypothesis under the neoclassical theory is also $\delta = 0$. In such a world the relative shock to the marginal product of labor is a sufficient statistic for worker flows, which is captured by γ alone. If, instead, internal labor markets matter for reallocation, then we should find a statistically significant δ. Internal labor markets can dampen ($\delta < 0$) or increase ($\delta > 0$) the sensitivity of worker flows to shocks, depending on the particular friction that makes internal labor markets matter.

Figure 2 shows the identification strategy behind coefficient δ. Firm A is the origin firm of the workers and firms B and C are two destination firms. For concreteness, assume both B and C face the same positive shock. The sole difference is that firms A and B belong to the same business group, while firm C is not affiliated to the group. The question is then whether the worker flow between A and B is larger than the worker flow between A and C. This captures the reallocation of workers in response to shocks, and not just average internal mobility. Figure 2 illustrates one possible scenario. Nothing guarantees that all destination firms face shocks, and even if destination firms face shocks, those shocks are not necessarily

[8] In Appendix A.2, which uses shocks to Tobin's Q in a broader sample, we show that our results are robust to including pair fixed effects.

[9] Our results are robust to clustering at the business-group level, i.e., instead of clustering at the level of the firms of origin and destination we cluster by the group affiliation of the firms of origin and destination.

positive. We allow the data to tell us whether worker flows follow the direction of shocks or not.

An example using the Angelini group from Figure 1 helps to further illustrate our empirical design. Arauco is wood pulp producer, while Corpesca is a fishmeal producer. Both are private firms. Suppose that the international price of pulp goes up, and the price of fishmeal stays constant. The relative shock between Arauco and Corpesca suggests a flow of workers going from Corpesca towards Arauco. The question that we ask is whether Corpesca sends more workers to Arauco than to other pulp producers that are not affiliated with the Angelini group. The regression also implicitly compares the flow of workers between Corpesca and Arauco with the flow towards destination firms in other industries (e.g., copper firms with a positive shock), and towards destination firms in the same industry but with a different export composition (e.g., the share of softwood and hardwood pulp being exported can vary across firms).

The problem with interpreting the coefficient on the same-group dummy (β) in a causal way is that group affiliation can be simultaneously determined with other variables. For example, firms that are geographically close or that operate in sectors that are industrially integrated can end up affiliated to the same business group. The response of affiliated firms to shocks (δ) should be less affected, although it is not immune to the simultaneity bias that affects the unconditional average. Shocks move at a higher frequency than ownership structures, so it is hard to argue that group affiliation is endogenous to particular shocks. The construction of shocks from international prices also assures that shocks are not endogenous to the labor flows themselves. However, the fact that group affiliation is not a choice variable, at the frequency in which shocks hit firms and labor flows take place, does not imply that group affiliation and labor flows cannot be jointly determined by other underlying forces.

In short, omitted variables represent the main source of endogeneity that we need to address. These omitted variables can interact with the shocks like group affiliation does. For example, in response to a shock, the worker flow between firms that operate in the same geographical area can be stronger than between firms that are far away. We address this possibility by adding interactions between shocks and other characteristics for pair of firms, such as geographical distance and industrial integration. Our tests show if group affiliation matters for between-firm reallocation above and beyond these other reallocation mechanisms that we observe and for which we can control for. However, we cannot fully rule out that some unobservable variable drives both group affiliation and labor flows in response to shocks.

Despite the endogeneity caveat, our results are still interesting to learn if affiliated firms behave differently from other firms of similar characteristics, or that experience similar shocks. Theory suggests that joint ownership can have positive or negative effects on the allocation of resources (Grossman and Hart 1986; Stein 1997; Scharfstein and Stein 2000; Duchin and Sosyura 2013). Hence, regardless of the motives that might drive affiliation, it is worth studying if, once affiliated, firms show a stronger or weaker response to shocks. The answer to this question is theoretically ambiguous, and so it becomes an empirical issue. Our results can give us hints regarding which effect dominates.

3.2 Main Results for Worker Flows

Table 3 reports the main results for equation (3.1). The coefficient on Same Business Group$_{do}$ implies that, when a group firm redeploys workers, the flow towards the average firm in the same group is 2.2 percentage points larger than towards the average unaffiliated firm (column 1). The effect is large and highly significant, accounting for close to half of the standard variation of worker flows (4.2%). Note that we control for the average wage in the origin and destination firms, which in principle should be a sufficient statistic to explain worker flows between firms. We also control for the level of employment of the origin and destination firms, together with the employment level and number of firms of the business groups involved (if the destination firm is also a group firm).

In columns 2 through 4 we focus on workers in different segments of the within-firm wage distribution. The effect of Same Business Group$_{do}$ is large and significant across segments. The coefficient grows in magnitude as we go from workers at the bottom quartile of the distribution (column 2) to workers at the top quartile of the distribution (column 4). However, since flows are more concentrated among top workers (see Table 2), the effect of Same Business Group$_{do}$ is similar when we compare it to the standard deviation of flows in each segment.

The interaction between the same-group dummy and export shocks is positive, but only marginally significant in the sample with all workers (column 1). When we split the sample by segments of the worker distribution, we find that the interaction term is practically zero for workers in the bottom quartile (column 2), but large and significant for workers in the top quartile (column 4). In response to a one-standard-deviation export shock, the average destination firm in the same group receives a flow of top workers that is 3.2 percentage points larger than the average unaffiliated destination firm (column 4). In comparison to the standard deviation of top worker flows, this implies that there is 20% (=0.032/0.160) more reallocation towards same-group firms than to unaffiliated firms in response to export shocks. Yet another way to understand this result is that the sensitivity of same-group top-worker flows to export shocks is 5 times (=0.032/0.006) the baseline sensitivity to export shocks among unaffiliated firms (0.006 from column 4).

To further expand our results, we also look at workers in the top 20th and 10th percentile of the within-firm wage distribution (columns 5 and 6). The effect is still large and significant despite the small samples. Finally, while the coefficient on the interaction between import shocks and the same-group dummy is negative as expected, the effect is not significant. This is consistent with exports being more relevant than imports, at least in our sample.[10]

[10] As further robustness of our main results in Table 3 we add as explanatory variables the lagged relative shocks (export and import), together with their interactions with the same group dummy. While the interaction term between the contemporaneous shock and the same group dummy remains significant, the interaction term between with lagged shocks is not statistically significant (see Table A.4). We also calculate the serial correlation of worker flows between years t and $t+1$. Although the serial correlation is statistically significant, the magnitude of the coefficient is small (less than 0.1; see Table A.5). Taken altogether, these results suggest that worker flows are not likely to persist in response to past shocks, nor quickly revert as in workers returning to their original firm.

3.3 Other Drivers of Reallocation

In our next test we control for other channels that may explain the higher levels of reallocation between group firms in response to export shocks. First, group firms may operate in more integrated industries, which can explain the larger flows of workers between them. We measure sector integration from the input-output matrix of the economy at the one-digit level, as published by the Central Bank of Chile. For each worker flow we compute integration as the average of: (i) the share of sales going from the industry of the origin firm to the industry of the destination firm, and (ii) the share of sales going from the industry of the destination firm to the industry of the origin firm. This measure can account, for example, for a large flow of workers between manufacturing and mining. Second, we compute the distance between the municipality of the origin firm and the municipality of the destination firm.[11] As in any gravity-type setup, firms that are far from each other are less likely to have large flows compared to firms that are geographically close.

In Table 4 we include interactions of sector integration and distance with the export shocks. For all workers (column 1), the interaction of sector integration and export shocks is positive, as expected, and statistically significant. However, the effect of integration is similar across segments of the wage distribution in contrast to the effect of the same-group dummy, which is focused on top workers. The interaction between distance and export shocks is negative for all types of workers except bottom-quartile workers. This can reflect a reluctance of workers above a certain level to move far away.

For our purposes, the most important result is the stability of the coefficient on the interaction between the same-group dummy and export shocks. This coefficient is barely affected with the inclusion of the new interactions. This suggests that the previously omitted variables of integration and distance are not the drivers of our results.

[11] Distance is measured between the headquarters of each firm, and in kilometers relative to the maximum distance in the country.

3.4 Effects on Wages and Promotions

In Table 5 we study the effects on the wages of workers that move between firms. We use the same regression specification as Equation (3.1) with the (log) change in the wage as dependent variable.

A first thing to note is that the coefficient on the same-group dummy is negative and relatively small for all workers (columns 1 and 2), but positive and large for top workers (column 5). This result adds to wage patterns documented in the previous literature on the internal labor markets of conglomerates. For example, Tate and Yang (2015) find that top workers gain the most from moving within diversified conglomerates. The 8.5 log points increase in wages for the top workers that move within the same group (column 5) is, however, only marginally significant.

The interaction of the same-group dummy and export shocks is negative and small for all workers (columns 1 and 2), but positive and large for top workers (column 5). The wages of top workers that move within the group following export shocks increase by 6.6 log points (column 5). The wage increase of the worker that moves could reflect a positive pass-through of shocks in the destination firm instead of a worker-specific effect. There is recent evidence that incumbent workers share some of the gains from firm-specific shocks (see Garin and Silverio 2018; Friedrich, Laun, Meghir, and Pistaferri 2019; Kline, Petkova, Williams, and Zidar 2019). To address this possibility we subtract from the wage change of the worker that is moving the wage change for the same type of worker that is staying in the destination firm ("stayers"). The wage increase of top movers is reduced to 4.8 percentage points (column 6), but it is still significant and economically large. This suggests that the result is associated to the worker that is moving, rather than simply a firm effect.

We do not have data on job categories, but we proxy for promotions with the change in within-firm wage ranking of the worker that moves. For example, a worker that is the fifth highest-paid worker in the origin firm and moves to be the second highest-paid worker in the destination firm would experience a promotion equal to three positions. Table 6 reports the results of Equation (3.1) using the change in wage ranking as dependent variable. The coefficient on the same-group dummy is small and insignificant for all workers (column 1). However, the interaction of the same-group dummy and export shocks is positive and significant (column 1), which suggests that the workers that move within the group following export shocks are climbing the corporate ladder. The effect is strongest for top workers (0.090 in column 4). Interestingly, the effect of import shocks on within-group top-movers is negative (-0.073 in column 4), and almost as large in magnitude as the positive effect of export shocks. Given downward rigidity in nominal wages, the wage ranking can potentially be a better proxy for reallocation in response to negative shocks.

3.5 Within-Group Worker Flows

A simple way to avoid the comparison between affiliated and unaffiliated firms is to restrict our attention to within-group flows. Following the winner-picking logic of Stein (1997), we test whether the owner of a group with firms A and B channels more scarce resources from A to B if the appeal of investing in B suddenly increases. This test is less ambitious than our previous test, which implicitly benchmarks the reallocation within affiliated firms to the reallocation with unaffiliated firms. Still, the within-group test addresses an important question. Namely, whether the allocation of resources between firms under a common owner follows market signals, such as export and import shocks, or not. Internal frictions (e.g., Scharfstein and Stein 2000; Duchin and Sosyura 2013) can mute market signals. Our previous results already suggest that business groups take market signals into account. However, by restricting attention to group firms we can avoid relying too heavily on the affiliated versus unaffiliated comparison.

We estimate the following within-group regression where firms d and o belong to the same business group:

$$\text{Worker Flow}_{dot}^{\text{Same Group}} = \beta \Delta \text{Export Price}_{dot} + \lambda' \text{X}_{dot} + \alpha_d + \alpha_o + \alpha_t + \epsilon_{dot}. \tag{3.2}$$

We report the results in Table 7. We find that group firms send more workers to the affiliated firms facing the most favorable export shocks (column 1), i.e., they are effectively picking winners. As before, the effect increases as we go from bottom-quartile workers (column 2) to top-quartile workers (column 4). The coefficient on export shocks for top workers is statistically significant at the 5% level despite the small sample. In terms of magnitude, a one-standard-deviation export shock induces a flow of 3.6% more top workers, which represents 17% the standard-deviation of top worker flows *within* group firms. These results suggest that the previous tables are not simply capturing some unobservable heterogeneity between affiliated and unaffiliated firms, but a real difference in worker reallocation.

3.6 The Extensive Margin

Our main regressions study the intensive margin of worker flows (i.e., the number of workers moving between two firms), and not the extensive margin (i.e., the likelihood of any worker moving between two firms). Ignoring the extensive margin could bias the estimation of the effects in the intensive margin (Wooldridge 2002). Dimensionality is one practical difficulty with the extensive margin, because the number of firm pairs with positive worker flows is small relative to the universe of possible firm pairs (i.e., less than 0.5%). In a manageable sub-sample we re-estimate Equation (3.1) using as dependent variable a dummy variable for firm pairs with a positive worker flow in a given year. The sample includes flows within and between industries that account for the largest share of worker flows in the economy (approximately 60%), i.e., mining, manufacturing, transportation and communications, wholesale trade, and retail trade. As with the intensive-margin regression, these regressions are conditional on the origin firm belonging to a business group.

The results are reported in Table 8. The coefficient on the same-group dummy is large and strongly significant across the table, meaning that firms in the same group are unconditionally more likely to exchange workers between them. More importantly, the interaction of same-group dummy and export shocks is positive and significant, meaning that it is more likely that firms in the same group exchange workers in response to shocks. The interaction effect is present in bottom-quartile and top-quartile workers alike. Hence, a potential bias arising from the extensive margin is unlikely to explain our previous results regarding the *differential* intensity on top-worker flows.

4 Why do Groups use Internal Labor Markets?

In the previous section we show that business groups actively use internal labor markets, in particular to transfer top workers in response to external shocks. We now explore the reasons for this internal labor mobility. Although financial constraints can explain the advantage of internal capital markets, they only imply an imperfect substitutability between internal and external funds, but not between internal and external workers. We study frictions that can break the perfect substitutability between internal and external workers.

In order to test for different frictions we study the heterogeneity of the effects in Equation (3.1). In practical terms, we add triple interactions between the same-group dummy, the export shocks, and proxies for each friction. We focus our attention on workers in the top-quartile of the wage distribution of the origin firm. The results are reported in Table 9.

4.1 Transaction Costs

A firm has to pay firing costs (e.g., severance payments) and hiring costs (e.g., head-hunting services, training, moving expenses) when redeploying or hiring workers to and from the external labor market. In terms of firing costs, Chilean firms have to pay twice as much as firms in OECD countries—a firm in Chile needs to pay 52 weeks of salary while a firm in the average OECD country only 26 weeks. Similarly, the difficulty hiring index is higher in Chile than in OECD countries. The OECD countries that are closer to Chile in terms of difficulty hiring are Mexico, Poland, Portugal, and Spain.[12]

[12] These differences in employment protection legislation can explain, to some extent, why the percentage of permanent workers in Chile is lower than in OECD countries – 83% and 88%, respectively- and why the

Although there are differences in labor protection when comparing across countries, there is little within-country variation that we could exploit for our tests. For instance, firing costs are the same for firms in the public and private sectors. Also, firing costs are independent of the firm's total number of employees.

For our purposes, the most interesting feature of Chilean labor legislation is that when a firm redeploys a worker to an affiliated firm the move is exempt from severance payments. This type of exemption is commonly observed in other countries (Belenzon and Tsolmon, 2016). Business groups can save on firing costs through this exemption. Hiring and firing are typically proportional to wages, which could in principle explain the stronger advantage of internal labor markets for top workers. At the same time, most of these costs are top-coded, which reduces their impact on the firm's bottom line. These costs can also be small relative to the productivity gains of reallocating top workers.

In order to test for the relevance of hiring and firing costs we use two proxies in Table 9. First, because severance payments are increasing in the tenure of the worker being fired, the transaction costs hypothesis predicts that internal labor mobility should be stronger for workers with longer tenure in an attempt to reduce firing costs. Workers with longer tenure are also likely to require less training. However, columns 2 and 3 show that the triple interactions with worker tenure in the origin firm, and with tenure in the same group, are small and not statistically significant. Thus, internal labor mobility is not stronger for longer-tenure workers.[13]

Second, we use geographical distance between the origin and destination firms as a proxy for search costs and moving expenses. Business groups might have an advantage in bridging between distant labor markets. However, column 4 in Table 9 shows that the triple inter-

turnover rate in Chile is considerable higher than in OECD countries- average tenure in OECD countries is ten years while average tenure in Chile is only four. Consistent with the hypothesis that temporary contracts can affect the training that workers receive, Chile lags behind OECD countries in terms of training - 33% of workers received training in OECD countries and only 23% in Chile.

[13] We also study the link between worker tenure and wage dynamics in Table A.6. We find that the wage change of movers is not larger for longer-tenure workers. The change in within-firm wage ranking of the worker that moves is also insignificant for workers with longer tenure. The evidence taken altogether suggests a limited role for firing cost in explaining our results.

action with distance is small and not significant, suggesting that the advantage of internal labor markets is not coming from connecting distant labor markets.

4.2 Imperfect Insurance

Business groups can provide implicit unemployment insurance to workers by offering greater job stability within the group in exchange for lower wages. At face value, the insurance hypothesis is not consistent with three of our results.

First, perfect insurance implies no pass-through of shocks to wages (Guiso, Pistaferri, and Schivardi, 2005), something that we can reject with the results shown in Table 5. Second, insurance should be more relevant for bottom-quartile workers because they have less access to consumption smoothing in financial markets (Blundell, Pistaferri, and Preston, 2008). Instead, our findings are more relevant for top workers. Third, we explore the heterogeneity of our result according to the nature of the shock. In particular, we look at "push" shocks, which we define as negative shocks at the origin firm. The response to push shocks should represent the lion's share of the results if the insurance motive is the main driver of internal mobility. This is partly the reason why the insurance literature is focused on plant closures and mass layoffs. We find, instead, that the triple interaction with the push dummy is negative, implying that there is less, instead of more, reallocation in response to push shocks (column 5 of Table 9).[14]

[14] In Appendix Tables A.7 and A.8 we dig deeper into the differences between push and pull shocks (positive shocks for the destination firm). We do not find differential effects of those shocks on worker flows, except for the effect of push shocks on top workers already reported in Table 9. We also check the effects of push and pull shocks on wage changes. As in the rest of the paper this analysis is performed only for workers that move between firms. There is a negative and marginally significant effect on wages of all workers in response to push shocks (column 1 of Appendix Table A.8). However, we do not find a differential effect of push or pull shocks on the wages of top workers, who are the focus of the rest of our results. The absence of an effect on flows of other workers, together with the lack of an effect on top worker wages, also suggest that our results are unlikely to be explained by insurance.

4.3 Skill Differentials

Another possibility is that internal mobility reflects skill differentials between workers in the internal and external markets. Skills may be hard to verify in external workers due to asymmetric information, so employers learn about the worker's true productivity only after hiring. Some skills may also be acquired exclusively after hiring (e.g., learning by doing). In both cases, internal workers are preferred by business groups because they have skills that are hard to verify in external workers, or that external workers do not have.

The question is then what types of skills drive internal mobility. The absence of a tenure effect (columns 2 and 3 in Table 9) suggests that job-specific skills are unlikely to be decisive. Industry-related skills may be more relevant for internal mobility. Tate and Yang (2015) argue that internal labor markets can smooth the transfer of human capital within an industry or between industries that require similar skills. First, we test this idea in column 6 of Table 9 with a triple interaction using a dummy for origin and destination firms that are in the same sector. The triple interaction is negative and not significant, implying that internal reallocation is not stronger within sectors. This suggests that the skills that are valuable for internal reallocation are not narrowly defined within an industry. Second, we add the triple interaction with the index of industrial integration from section 3.3. The coefficient on this triple interaction is positive, as expected, implying that there is more internal reallocation in response to shocks when sectors require similar skills because they are more integrated. The coefficient on the triple interaction is, however, not statistically significant (column 7). We interpret this evidence as saying that the skills that drive internal mobility are not necessarily correlated with the industrial process.

Our evidence is, therefore, most consistent with the value of general skills. Recent literature has emphasized the rising importance of general skills (Frydman 2020; Kaplan, Klebanov, and Sorensen 2012). General skills, such as managerial practices, are key factors of production (Bloom, Eifert, Mahajan, McKenzie, and Roberts 2013; Atalay, Hortaçsu, and Syverson 2014). Cross-firm differences in managerial practices are highly persistent (Bloom and Van Reenen 2007), which suggests that they cannot be easily acquired from the market. Our finding that reallocation is focused on top workers is consistent with the importance of general skills, since these skills are more relevant for top workers (Deming and Kahn 2018).

In column 8 of Table 9 we show evidence consistent with the importance of general skills. We find that internal mobility for top workers is more pronounced when the origin firm controls the destination firm; that is, when the top worker is being transferred from above in the hierarchical structure (e.g., from Antarchile to Copec in Figure 1). Since there is positive sorting in hierarchies (Garicano and Rossi-Hansberg 2006), this suggests that the worker is better endowed with general skills (or "knowledge" in the language of the hierarchies literature). One can also imagine that general skills are more easily acquired or screened for in higher levels of the control hierarchy. This result is also potentially consistent with Tate and Yang (2015) since firms that are related by a control link are more likely to share an organizational culture and strategy. Workers are more easily transferred to redeploy their skills when the two firms are similar along these dimensions, even if the firms operate in different industries.[15]

Family firms are sometimes more prone to agency problems and nepotism (Pérez-González 2006). If family business groups drive our results, then it would be at least suggestive evidence against the skill hypothesis. In column 9 of Table 9 we add a triple interaction with a dummy for groups where the controlling shareholder is a family (as opposed to controlling shareholders such as foreign investors, the state, or others). We find that the triple interaction is small and not significant, suggesting that low-skill family members are unlikely to drive our results.

Overall, our results are most consistent with the idea that labor flows reflect stronger general skills of internal workers. Admittedly, the proxies for frictions that we use in this section are coarse. Our results are more consistent with some frictions than others, but we

[15] We also study the link between control of the origin firm over the destination firm and changes in wages and wage-rankings of movers. In Table A.6 we find that, although coefficients are positive, there is no statistical significance in the triple interaction.

cannot rule out any of them. Different frictions can also operate simultaneously to favor internal mobility in business groups.

5 Firm-level Effects of Internal Labor Mobility

Finally, we study the effect of internal labor market mobility on firm-level outcomes. We do not have access to standard financial variables for most of the firms in our sample since they are private firms. Hence, we can only focus on rough proxies of productivity. Partly for this reason, we view the evidence in this section as only suggestive.

We study whether the arrival of a top worker from within the business group creates value in the destination firm. Firms that receive a top worker from within the group are *treated* firms in our experiment. If the new worker is endowed with more skills, and if she is in a top position, she can potentially have an impact on the entire firm. As shown by Bloom, Eifert, Mahajan, McKenzie, and Roberts (2013), better managerial practices can have large effects on firm-level productivity. Hence, the evidence in this section also speaks about the frictions described in the previous section, and in particular, about skill differentials versus other frictions. In the same vein as Tate and Yang (2015), our results can help explain productivity differentials between affiliated and non-affiliated firms (e.g., Schoar 2002).

We implement an event study where we compare the productivity of treated firms with the productivity of control firms. *Control* firms are standalone or group firms that receive a top worker from an unaffiliated firm. We follow the strategy of Abadie and Gardeazabal (2003), and Abadie, Diamond, and Hainmueller (2010), and we build a synthetic control for each treated firm out of the sample of all potential control firms. In order to build the synthetic control we use a 3-year window before firms receive the top worker. The weights on the synthetic control are defined by a minimum distance approach based on firm-level international shocks, industry, employment level, and dummies for being an exporter and importer. Both treated and control firms are receiving international shocks in our experiment. The average effect is computed as the average cumulative difference between the treated firms and the synthetic controls for years 0 through 3, where year 0 is the year during which the firm receives the top worker.

Figure 3 and Table 10 report the results. In Panel A we measure productivity as net exports (exports minus imports) over the wage bill of the firm. This measure combines data from customs with the unemployment insurance database. Treated and control firms are virtually indistinguishable in the years before the arrival of the top worker, which supports the idea that this is a clean comparison. Treated firms are more productive after the arrival of the top worker. On average over the next 4 years (years 0 through 3), net exports over wage bill are 45% higher in firms that receive a top worker from the same business group. The strong statistical significance of this difference can be seen in Table 10. In Panel B we measure productivity as net exports per employee. There is barely any difference between treated and control firms before and immediately after the arrival of the top worker. However, the advantage of treated firms appears strongly in years 2 and 3. On average over years 0 through 3, treated firms have $1,340 more net exports per employee.

Next, we use the firm's wage per employee as measure of productivity. Panel C shows an increase in the average wage of the treated firms, while control firms show a slight decrease. The difference between treated and control firms is 12.3% in the period after the arrival of the top worker. As we show in Table 5, there is an increase in the wage of the top worker that moves to a destination firm within the group. This could mechanically explain the increase in the average wage of the firm receiving this worker. To address this issue in Panel D we show the average wage of the destination firm excluding the top worker that arrives. Although smaller, the difference of 9.4% remains large and highly significant. This is consistent with the idea that the movement of the top worker has a positive spillover on the productivity of the other workers in the firm (Jarosch, Oberfield, and Rossi-Hansberg 2018).[16]

[16]In the spirit of Faccio and O'Brien (2017) we also run reduced-form regressions of firm-level wage and employment growth on export shocks, and the interaction between the shocks and a business-group indicator. We report the results in appendix Table A.9. We find that wage growth is more responsive to export shocks in group firms, but employment growth is less responsive. Higher wage growth and lower employment growth

In sum, the arrival of a top-worker from within the same business groups is associated with higher productivity along several dimensions. Our results suggest that internal labor mobility adds value by reallocating top workers across group firms. These results also support the idea that top workers from the same group are endowed with more skills in comparison to top workers from the external labor market.

Two caveats are still worth reminding. First, we would like to have better data to look at standard proxies of productivity such as profits or TFP. Second, although the synthetic control methodology is relatively clean in terms of accounting for observable differences between firms, we cannot claim that there are no unobservable factors affecting our comparisons.[17]

6 Conclusions

Business groups –legally independent firms controlled by the same ultimate shareholder– are common corporate structures around the world. There are several reasons that explain the existence of these complex ownership structures. In this paper we focus on the use of internal labor markets. Business-group firms, unlike standalone firms, have the option of redeploying workers within the group, which could be better than relying on external labor markets. Using a matched employer-employee dataset for Chile we provide novel micro evidence of strong labor mobility inside business groups. Worker flows between group firms are significantly more prevalent than with unaffiliated firms.

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suggest increasing productivity as a response to export shocks. For the limited sample of listed firms we find that profitability (ROA, ROE) goes up with export shocks. Finally, we find that group affiliation makes labor hiring and churning (hiring plus firing) less responsive to export shocks. Firing is also less responsive to export shocks, as could be expected from an insurance perspective, but the relevant coefficient on the interaction of export shocks and the group dummy is not statistically significant.

[17] We perform two types of robustness checks for the results presented in Table 10. First, in Appendix Table A.10 we present results using the nearest-neighbor matching with Mahalanobis metric (Abadie, Drukker, Herr, and Imbens 2004). The results are even stronger in magnitude than with synthetic controls, and of comparable statistical significance. Second, in Appendix Table A.11 we show treatment effects for a subset of cases that involve push shocks, and when the origin firm controls the destination firm. The results show a positive and significant effect on all performance measures (net exports per employee, net exports over wage will, average wage, and the average wage of stayers) in these two cases. The magnitude of the treatment effect is somewhat larger than in the base case reported in Table 10, but it is also noisier since these are smaller samples.

We study the reallocation of workers in response to changing business conditions, measured by firm-level changes in international export (and import) prices. International prices have the advantage of being plausibly exogenous to worker flows and firm characteristics in a small and open economy. We find that, in response to shocks, group firms send more top workers to firms in the same group than to unaffiliated firms. The wages of those workers increase as they move within the group, and they reach higher positions. We find that firm-level productivity increases with the arrival of a top worker from within the same group. Hence, our results suggest that internal labor mobility adds value by reallocating top workers across group firms.

Regarding the potential drivers of internal labor mobility, our results are consistent with the importance of general management skills. Joint ownership between firms facilitates the transfer of top workers that are well-endowed with general skills. This explanation is not mutually exclusive with other labor-market frictions, and although we do not find evidence in support of these other frictions, we cannot rule them out completely.

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Appendix

A.1 Data Appendix

This appendix describes in detail the datasets used in the paper and the cleaning procedures and merging procedures used.

Limitations of Unemployment Insurance Dataset. Wage records are subject to three important limitations. First, they include only workers who have formal contracts with employers. According to standard estimates of the main employment survey in Chile carried out by the Institute of National Statistics, around 83% of dependent employment is formal in Chile, one of the highest in the region. Second, they include only workers who signed their contracts after 2002. Thus, workers with formal contracts that either (i) started working after 2002, (ii) changed formal jobs after 2002 and/or (iii) renegotiated any contract characteristic after 2002, should be in the dataset. Since 2002, the coverage of the dataset has been increasing. In fact, aggregate employment that appears in the unemployment insurance (UI) dataset in 2015, i.e., around 4.6 million, is less than the population that contributes to pension funds, 5.1 million, which is not affected by the constraints of the dataset. Nevertheless, workers contributing to pension funds include public workers, which are around 600,000. Thus, by 2015, aggregate employment of the dataset is approximately the same as the one reported by pension funds administrators. Third, wages are top-coded at a certain threshold. Around 4% of workers were top-coded in their main jobs in 2015, which represents around 20% of firms' aggregate wage expenditures.[18]

Cleaning Process of Unemployment Insurance Dataset. We implement a set of cleaning filters to the dataset that are standard in the literature (Song, Price, Guvenen, Bloom, and Von Wachter 2015; Card, Heining, and Kline 2013). First, we drop firms that have less than 5 workers. These represent around 2/3 of the total number of firms and represent around 8% of total employment in 2015. We drop these firms because the identification of a firm in the dataset is done through tax IDs. Thus, there might be concerns that tax IDs with few workers might not be firms but, e.g., shell corporations for tax purposes. This decision also helps to make more meaningful the statistics of within-firm distribution of workers and it follows the restrictions applied in matched employer-employee datasets. Second, we focus on spells at the highest-paying jobs for each individual in each year. This implies dropping around 17% of total job spells per year. Regarding workers that have several jobs, the income of their main jobs represents around 90% of their total labor income across jobs in 2015. Third, we exclude workers that have a weak labor attachment. That is, we exclude workers that earn less than a quarter of the annual equivalent of the minimum wage. These workers represent around 15% of employment and around 1% of firms' aggregate wage expenditures in 2015. Given these restrictions, we end up with a dataset of around 100,000 employers and 4.6 million workers.

Business Groups Dataset Limitations. Chilean financial statements for public firms report the list of consolidating entities, which include those with direct and indirect ownership. So, if firm A owns, and hence consolidates with firm B, and in turn firm B owns

[18] This number represents a lower bound due to the fact that wages are censored for top-coded workers.

and consolidates with firm C, then the statements of firm A will also name firm C under the list of consolidating entities. We also redo the list at the group level by adding up all the available consolidation lists of individual public firms in the group. For example, we put together the consolidation lists for firm A and firm B (if both are public), just in case that the list for firm A has errors and omissions. The same is done with the list of related investments for all the public firms in the group.

Two caveats about the ownership data are in order. First, our business group data excludes financial firms (commercial banks, mutual fund companies, pension fund administrators, etc.). This is not a big omission for our purposes because ties between business groups and banks have been limited by regulation since the aftermath of the debt crisis in the 1980s. Second, although we are able to identify the private firms that belong to each group, we do not know the direct ownership stake between pairs of private firms in the group. For example, if X is a listed firm, and Y and Z are private firms that consolidate with X, then we know that X, Y, and Z belong to the same group. We also know the stake between X and Y. However, we do not know the stake between Y and Z.

Merge of the Labor Dataset with the Business Group Dataset. As with the employer-employee dataset, firms in the business groups data are identified with unique tax IDs. We use these unique identifiers to merge both datasets. From the business group dataset, around 45% of firms are on average across years in the employer-employee dataset. From the aforementioned cleaned employer-employee dataset, around 0.3% of firms across years are in the business group dataset. These firms represent on average about 3% and 5% of aggregate employment and wage bill, respectively. At the same time, these firms represent close to 80% of the stock market capitalization of the Chilean market, and their total revenue over GDP is almost 60%.

COMTRADE dataset. This dataset is organized and cleaned by the Centre d'Etudes Prospectives et d'Informations Internationales (CEPII, for its acronym in French). CEPII organizes COMTRADE's database into BACI, which is a cleaned version of COMTRADE's database. This dataset, identifies the value and quantity for each 6-digit HS product and country that is traded globally. This dataset is merged to the firm-level international trade dataset using unique HS codes and country IDs.

Merge of the Customs Dataset with the Labor Dataset. Once the international price shocks are created at the firm level, the international trade dataset is merged at the firm level with the unemployment insurance and group data using firms' unique tax IDs. It is important to note that, due to confidentiality restrictions, this merge is not implemented by the authors. In fact, the authors in this paper do not have direct access to the merged datasets. Only staff of the Central Bank of Chile can work with the merged datasets in a secure server once all tax IDs are erased and replaced with fake IDs. Furthermore, all the moments that are documented in this paper have been revised in order to meet the data agreement standards so that no individual tax ID can be identified. This guarantees anonymity and the confidentiality of the dataset.

From the trade dataset, around 45% of firms that either export or import are merged with the UI dataset on average across years. These firms that are merged account for around 98% and 95% of export and import flows, respectively. From the cleaned UI dataset, around 4% and 15% of firms export and import, respectively. Among firms that are merged, importers account for around 38% and 50% of employment and aggregate wage bill, respectively, whereas exporters account for 15% and 25%, respectively. Among firms that appear in both the UI and trade dataset, 73% are only importers, 6% are only exporters and 21% do both. Firms that do both activities account for 97% and 72% of aggregate exports and imports, respectively.

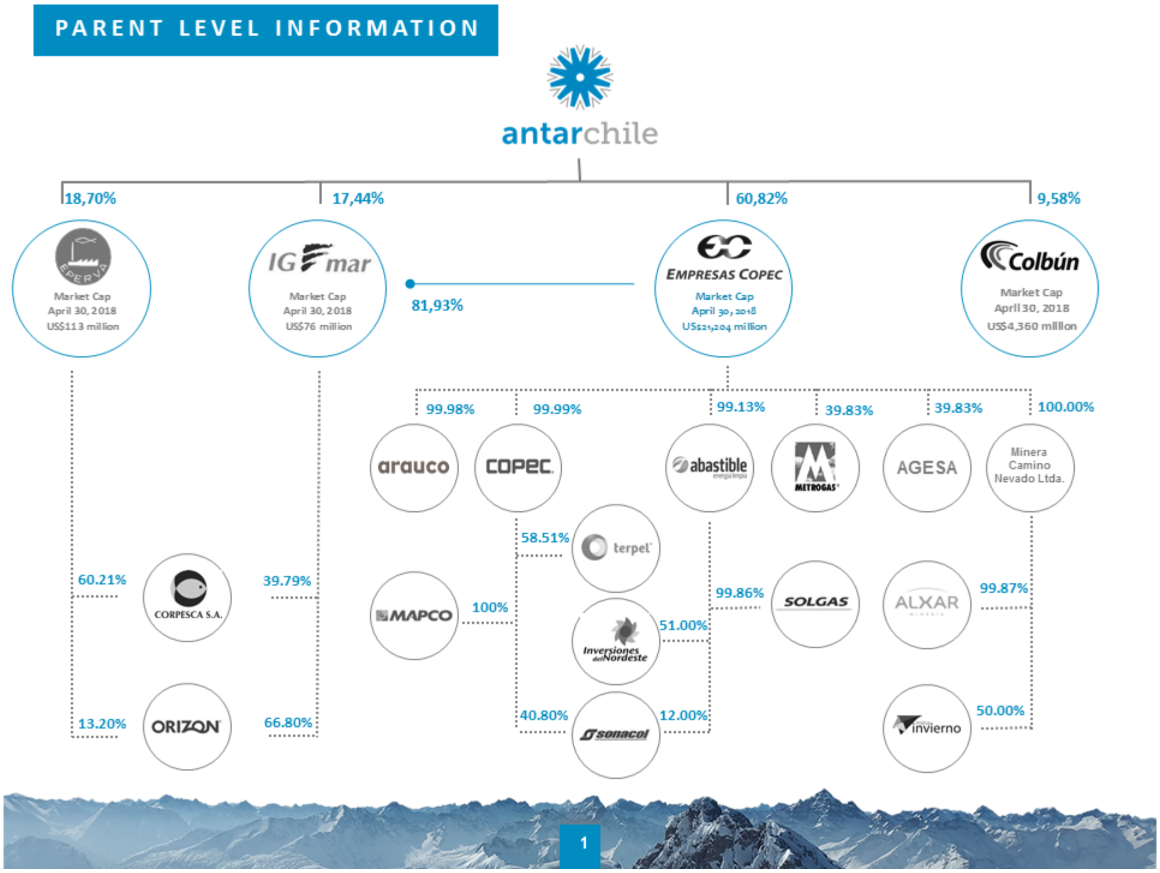
A.2 Shocks to Tobin's Q

We now follow the finance literature and use changes in *industry*-level Tobin's Q as our measure of shocks (Tate and Yang, 2015). We collect data from Economatica, which provides financial statements and stock market information for the universe of listed firms in Chile. For each listed firm, we compute Tobin's Q as the ratio between the market and book value of assets. The market value of assets is equal to the market value of equity plus the book value of debt. Next, we calculate the average Tobin's Q across all listed firms in each industry each year. We use the industry classification given by the employer-employee data at the two-digit level (20 industries). Finally, for each firm in our employer-employee dataset (listed and private), we define the shock as the percentage change in Tobin's Q for the industry to which the firm belongs. Besides endogeneity concerns of Tobin's Q, specially for business group firms that account for a large fraction of listed firms, perhaps the biggest drawback is that Tobin's Q shocks are relatively coarse. We lose the granularity of the trade shocks used in the main text, which we measure at the firm level instead of the industry level. By construction, there are no within-industry shocks when we use Tobin's Q. Tobin's Q shocks are also more relevant for listed firms rather than private firms, which represent the lion's share of our employment data.

Table A.12 reports the results for Equation (3.1) using as shocks the difference in Tobin's Q growth for each firm's industry. The interaction term between the same group dummy and the relative shock is positive but not significant for the sample of all workers (column 1). The effect becomes large and statistically significant at the 5% level for workers at the top quartile of the within-firm wage distribution (column 7). To interpret the magnitude of the effect, consider an origin group firm that faces a one-standard-deviation relative negative shock. The average destination firm in the same group receives a flow of top workers that is 2.4 percentage points larger than the average unaffiliated destination firm. Relative to the standard deviation of top-worker flows, this result means that there is 12% more reallocation towards same-group firms than to unaffiliated firms in response to Q shocks (=0.024/0.205).

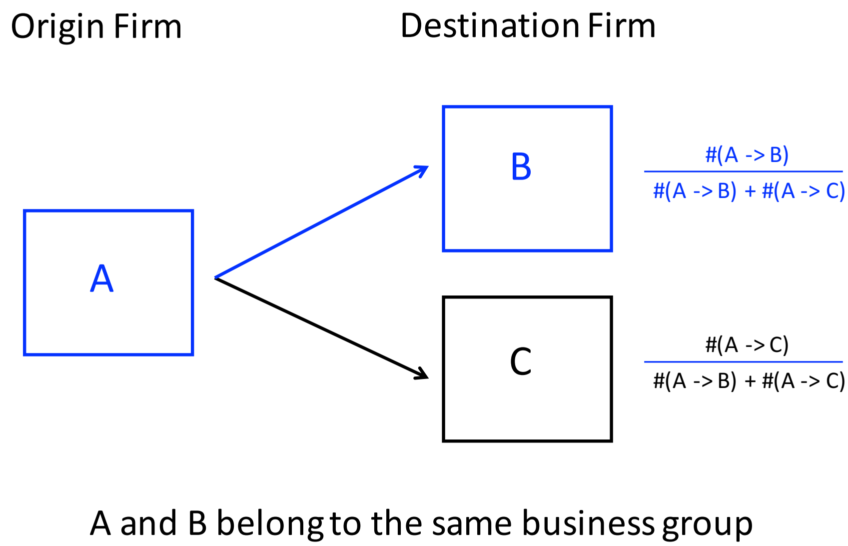
The sample with Tobin's Q is larger, hence it allows us to include firm-pair fixed effects and control for all time-invariant differences between affiliated and unaffiliated pairs. By including firm pair fixed effects we compare the response to shocks *within* pairs of affiliated and unaffiliated firms. The even columns in Table A.12 report the results of estimating Equation (3.1) with firm-pair fixed effects. This regression is identified on the basis of repeated worker flows between pairs of firms over time. For this reason, the number of observations decreases from around 50,000 to 24,000 (compare columns 1 and 2 of Table A.12). The regression confirms the finding that group firms actively use internal labor markets, especially for top workers. In fact, the coefficients on our interaction of interest are not statistically different when comparing regressions with and without pair fixed effects. This suggests that the results are not driven by unobserved heterogeneity between affiliated and unaffiliated pairs.

Figure 1: Example of the Ownership Structure of a Business Group: Antarchile



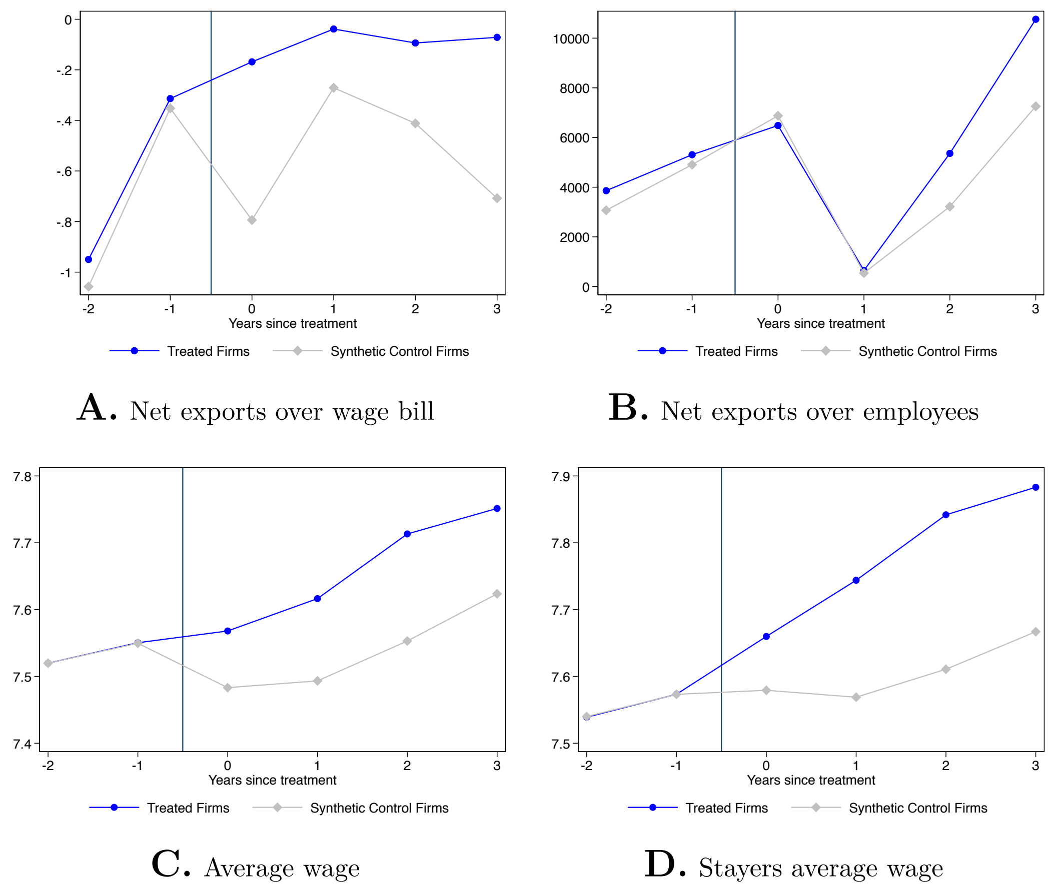
Notes: This figure presents the ownership structure of Antarchile, one of the largest business groups in Chile and controlled by the Angelini family.

Figure 2: Illustration of Internal Labor Reallocation



Notes: This diagram illustrates the identification strategy used in the paper (see Section 3.1). Firms A and B belong to the same business group, while firms A and C are unaffiliated. Assume firms B and C face a positive shock. We compare $\frac{\#(A \to B)}{\#(A \to B)+\#(A \to C)}$ to $\frac{\#(A \to C)}{\#(A \to B)+\#(A \to C)}$, where $\#(A \to B)$ denotes the number of workers moving from firm A to firm B, and $\#(A \to C)$ denotes the number of workers moving from firm A to firm C.

Figure 3: Impact of Receiving a Top Worker



A. Net exports over wage bill

B. Net exports over employees

C. Average wage

D. Stayers average wage

Notes: The figure shows the evolution of net exports (exports minus imports), and log average wages for treated firms and for synthetic control firms. Treated firms are business group firms that receive a top worker from the same business group. Synthetic control firms are firms, in a group or standalone, that receive a top worker from a firm that is not affiliated. Panel A shows results for net exports over the firm's wage bill, while Panel B shows the results for net exports over the firm's number of employees. In Panel C average wage is computed using all the workers of the firm, while in Panel D it is computed using workers that worked at the firm before the treatment (stayers). The choice of synthetic controls is discussed in Section 5.

Table 1: Summary Statistics for Number of Firms, Workers, and Firm Pairs

Number of Firms	Mean per Year	Total
All	66,001	198,670
Business Group	236	310
Standalone	65,765	198,360
Number of Workers	**Mean per Year**	**Total**
All	3,309,022	6,881,912
Business Group	103,308	332,851
Standalone	3,205,714	6,811,616
Number of Workers per Firm	**Mean per Year**	**Total**
All	50	35
Business Group	438	1,074
Standalone	49	34
Number of Firm Pairs	**Mean per Year**	**Total**
All	2,475	22,789
Same Business Group	160	1,038
Unaffiliated	2,315	21,751

Notes: This table reports statistics for the number of firms, number of workers, number of workers per firm, and number of firm pairs with employment flows, for our sample of Chilean firms (2004-2015). We report the average per year and the total number of unique values of each variable in our sample. Firms can be in a business group or standalone. All firm pairs have a group firm as origin firm. Destination firms can be in the same group or unaffiliated (in other business groups or standalone firms).

Table 2: Summary Statistics for Worker Flows and Wage Changes of Movers

		Means (across firm-pair-years)			
			by quartiles of wage distribution		
	Pairs of Firms	All	Bottom 25	Mid 50	Top 25
Worker Flow (%)	Same Business Group	5.3	8.1	10.7	19.8
	Unaffiliated	1.9	3.6	4.4	11.6
Number of Employees Sent	Same Business Group	3.6	2.0	3.4	2.6
	Unaffiliated	1.3	1.2	1.3	1.2
Wage Changes of Movers (%)	Same Business Group	5.1	10.0	2.0	6.1
	Unaffiliated	-3.2	0.2	-6.0	-6.2

Notes: This table reports averages across all firm-pair-years of worker flows and wage changes of employees that move between firms. The worker flow is the number of workers sent by the origin firm to a particular destination firm relative to the total number of workers sent by that origin firm to all destination firms in a year. All origin firms are group firms. Destination firms can be in the same group or unaffiliated (in other business groups or standalone firms). We present flows for all workers, and for those in the bottom quartile, middle quartiles, and top quartile of the within-firm wage distribution of the origin firm.

Table 3: International Trade Shocks and the Internal Labor Markets of Business Groups

	All Workers	Bot. 25 Workers	Mid. 50 Workers	Top 25 Workers	Top 20 Workers	Top 10 Workers
	(1)	(2)	(3)	(4)	(5)	(6)
Same Business Group	0.022***	0.018***	0.024**	0.044***	0.052**	0.016
	(0.006)	(0.007)	(0.010)	(0.016)	(0.023)	(0.030)
Same Business Group x ΔExport Price	0.004*	-0.000	0.008	0.032**	0.027*	0.091***
	(0.002)	(0.002)	(0.005)	(0.013)	(0.014)	(0.029)
Same Business Group x ΔImport Price	-0.004	-0.009	-0.015*	-0.004	0.002	-0.002
	(0.004)	(0.007)	(0.009)	(0.012)	(0.012)	(0.020)
ΔExport Price	0.001	0.001	0.002	0.006	0.001	-0.018
	(0.001)	(0.001)	(0.002)	(0.004)	(0.005)	(0.012)
ΔImport Price	-0.001	0.001	-0.001	-0.002	-0.005	-0.003
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.008)
Log Avg. Wage Origin	0.003	0.016	-0.012	0.046	0.051	0.254**
	(0.018)	(0.018)	(0.017)	(0.080)	(0.079)	(0.120)
Log Avg. Wage Destination	0.000	-0.001	-0.002	-0.057	-0.066	-0.103
	(0.003)	(0.005)	(0.008)	(0.038)	(0.046)	(0.082)
Log Employment Destination	-0.002*	-0.004**	-0.006*	-0.022**	-0.027**	-0.057***
	(0.001)	(0.002)	(0.003)	(0.010)	(0.012)	(0.018)
Log Employment Origin	-0.046***	-0.086***	-0.074***	-0.158***	-0.192***	-0.256***
	(0.009)	(0.017)	(0.012)	(0.030)	(0.030)	(0.040)
Log Emp. Business Group Origin	-0.083	-0.281	-0.149	0.301	0.267	0.429
	(0.079)	(0.175)	(0.248)	(0.326)	(0.426)	(0.609)
Log Emp. Business Group Destination	-0.119**	-0.287***	-0.137	-0.209	0.011	0.721
	(0.049)	(0.099)	(0.143)	(0.215)	(0.297)	(0.728)
Log N. Firms Business Group Origin	0.068*	0.098*	0.081**	0.390**	0.404**	0.376
	(0.037)	(0.056)	(0.039)	(0.168)	(0.184)	(0.280)
Log N. Firms Business Group Destination	0.013	0.018	0.030	-0.029	-0.033	0.590
	(0.016)	(0.021)	(0.032)	(0.171)	(0.224)	(0.881)
R^2	0.594	0.680	0.639	0.697	0.688	0.758
Origin FE	✓	✓	✓	✓	✓	✓
Destination FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Mean DV	.02	.037	.047	.122	.144	.23
SD DV	.042	.066	.084	.16	.181	.249
Mean Numerator DV	1.3	1.1	1.3	1.5	1.4	1.4
Number of observations	20188	9184	7523	2457	1974	922

Notes: This table reports results for the OLS regression in Equation (3.1). The dependent variable (DV) is the worker flow for all workers (column 1), and for workers in different segments of the within-firm wage distribution of the origin firm (columns 2-6). All origin firms are group firms; destination firms can be group firms or standalone firms. Same Business Group is a dummy that takes the value of one for those pairs of firms where the origin and the destination are part of the same business group. Δ Export Price (Δ Import Price) is defined as the difference in firm-level export (import) price shocks between the destination and origin firms. Log Avg Wage Origin (Destination) is the log average wage in the firm of origin (destination). Log Employment Origin (Destination) is the log total number of workers in the firm of origin (destination). Log Emp or N Firms Business Group Origin (Destination) is the log total number of workers or firms in the business group of the firm of origin (destination). Group-destination variables are set to zero if the destination firm is a standalone (we include a separate dummy for these cases). Regressions include fixed effects (FE) for the origin firm, destination firm, and year. Mean Numerator DV is the average of the numerator of the dependent variable (i.e., the average number of employees sent to a destination firm). Robust standard errors in parentheses are double clustered at the level of the firm of origin and destination of the flow. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: International Trade Shocks and Other Drivers of Reallocation

	All Workers	Bot. 25 Workers	Mid. 50 Workers	Top 25 Workers	Top 20 Workers	Top 10 Workers
	(1)	(2)	(3)	(4)	(5)	(6)
Same Business Group	0.022***	0.018***	0.025**	0.042**	0.052**	0.022
	(0.006)	(0.006)	(0.010)	(0.016)	(0.023)	(0.030)
Same Business Group x ΔExport Price	0.004**	0.001	0.008	0.033***	0.026*	0.068**
	(0.002)	(0.002)	(0.005)	(0.012)	(0.013)	(0.029)
Sector Integration x ΔExport Price	0.008**	0.006	0.006	0.014	0.006	-0.062
	(0.004)	(0.004)	(0.008)	(0.016)	(0.019)	(0.051)
Distance x ΔExport Price	0.001	0.003	-0.019*	-0.022	-0.027	-0.129*
	(0.003)	(0.005)	(0.011)	(0.022)	(0.038)	(0.072)
Same Business Group x ΔImport Price	-0.004	-0.010	-0.014*	-0.004	0.003	0.005
	(0.004)	(0.006)	(0.008)	(0.012)	(0.012)	(0.025)
ΔExport Price	-0.001	-0.001	0.002	0.005	0.001	0.004
	(0.001)	(0.001)	(0.002)	(0.005)	(0.006)	(0.017)
ΔImport Price	0.001	0.003**	0.002	0.003	0.004	0.011
	(0.001)	(0.001)	(0.002)	(0.004)	(0.005)	(0.014)
Log Avg. Wage Origin	0.004	0.016	-0.010	0.050	0.053	0.274**
	(0.018)	(0.018)	(0.017)	(0.080)	(0.080)	(0.122)
Log Avg. Wage Destination	0.000	-0.001	-0.002	-0.057	-0.068	-0.075
	(0.003)	(0.005)	(0.008)	(0.038)	(0.046)	(0.084)
Log Employment Destination	-0.002*	-0.004**	-0.006*	-0.022**	-0.028**	-0.049**
	(0.001)	(0.002)	(0.003)	(0.010)	(0.011)	(0.019)
Log Employment Origin	-0.046***	-0.086***	-0.072***	-0.158***	-0.191***	-0.242***
	(0.008)	(0.017)	(0.012)	(0.030)	(0.030)	(0.040)
Log Emp. Business Group Origin	-0.082	-0.284	-0.152	0.310	0.250	0.201
	(0.078)	(0.174)	(0.247)	(0.328)	(0.433)	(0.623)
Log Emp. Business Group Dest.	-0.119**	-0.294***	-0.128	-0.220	0.001	0.487
	(0.049)	(0.099)	(0.145)	(0.208)	(0.299)	(0.723)
Log N. Firms Business Group Origin	0.067*	0.098*	0.076*	0.390**	0.415**	0.457
	(0.037)	(0.055)	(0.038)	(0.167)	(0.182)	(0.283)
Log N. Firms Business Group Dest.	0.013	0.017	0.030	-0.031	-0.032	0.619
	(0.015)	(0.020)	(0.032)	(0.168)	(0.221)	(1.094)
R^2	0.596	0.681	0.640	0.699	0.689	0.751
Origin FE	✓	✓	✓	✓	✓	✓
Destination FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Sector-Yr FE						
Mean DV	.02	.037	.047	.122	.144	.233
SD DV	.042	.066	.084	.16	.181	.251
Mean Den. DV	1.2	1.2	1.3	1.1	1.1	1.1
N	20188	9184	7523	2459	1976	923

Notes: This table shows results when adding interactions of sector integration and distance with export shocks. See Table 3 for the main regression specification and the definition of the variables. We measure sector integration from the input-output matrix of the economy at the one-digit level (Central Bank of Chile). For each worker flow we compute the share of sales going from the industry of the origin firm to the industry of the destination firm. Distance is measured between the municipality of the origin firm and the municipality of the destination firm. Robust standard errors in parentheses are double clustered at the level of the firm that sends and receives the flow. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: International Trade Shocks and Wage Changes of Movers

	All Workers		Bot. 25	Mid. 50	Top 25	Top 25 vs Stayers Dest.
	(1)	(2)	(3)	(4)	(5)	(6)
Same Business Group	-0.003	-0.005	-0.026	0.012	0.085*	0.075
	(0.021)	(0.022)	(0.038)	(0.041)	(0.046)	(0.052)
Same Business Group x ΔExport Price	-0.001	-0.001	-0.012	0.006	0.066***	0.048**
	(0.008)	(0.007)	(0.012)	(0.013)	(0.021)	(0.023)
Same Business Group x ΔImport Price	0.011	0.009	0.026	0.005	0.009	0.004
	(0.011)	(8.057)	(4.033)	(0.008)	(0.014)	(0.016)
ΔExport Price	0.000	-0.000	0.005	-0.002	-0.009	-0.002
	(0.003)	(0.003)	(0.005)	(0.005)	(0.008)	(0.009)
ΔImport Price	-0.008**	-0.009**	-0.005	-0.009	-0.007	-0.007
	(0.004)	(0.004)	(0.005)	(0.006)	(0.008)	(0.008)
Log Avg. Wage Origin		-0.431***	-0.609***	-0.538***	-0.450***	-0.441***
		(0.033)	(0.044)	(0.047)	(0.056)	(0.054)
Log Avg. Wage Destination		0.100**	0.042	0.060	0.072	0.317***
		(0.041)	(0.035)	(0.043)	(0.083)	(0.090)
Log Employment Destination		-0.011	-0.049**	-0.015	-0.008	-0.049
		(0.016)	(0.022)	(0.017)	(0.027)	(0.030)
Log Employment Origin		-0.057***	-0.034**	-0.044***	-0.055**	-0.050*
		(0.008)	(0.014)	(0.011)	(0.026)	(0.026)
Log Emp. BG Origin		0.230	0.047	0.451	-0.665	-0.476
		(0.334)	(0.384)	(0.441)	(0.629)	(0.753)
Log Emp. BG Dest.		0.088	0.369	0.275	-0.619	0.676
		(0.334)	(0.389)	(0.418)	(0.500)	(0.464)
Log N. Firms BG Origin		-0.008	-0.050	-0.136	-0.071	0.236
		(0.185)	(0.148)	(0.184)	(0.358)	(0.353)
Log N. Firms BG Dest.		0.187	0.162	0.266	0.383	0.195
		(0.192)	(0.206)	(0.216)	(0.428)	(0.428)
R^2	0.458	0.465	0.527	0.567	0.524	0.548
Origin FE	✓	✓	✓	✓	✓	✓
Destination FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Mean DV	.199	.2	.243	.176	.134	.087
SD DV	.411	.411	.428	.404	.356	.374
N	20970	20012	7384	9274	2608	2516

Notes: The dependent variable is the log change of wages for the workers that move (movers) between the destination and the origin firm. See Table 3 for the main regression specification and the definition of the variables. Column 6 has the same dependent variable as column 5, with the exception that it subtracts the log change of wages for stayers in the destination firm. Robust standard errors in parentheses are double clustered at the level of the firm that sends and receives the flow. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: International Trade Shocks and Changes in Wage-Ranking of Movers

	All Workers	Bot. 25	Mid. 50	Top 25
	(1)	(2)	(3)	(4)
Same Business Group	0.006	-0.053	0.010	0.039
	(0.066)	(0.106)	(0.072)	(0.066)
Same Business Group x ΔExport Price	0.055*	0.033	0.019	0.090**
	(0.028)	(0.032)	(0.027)	(0.043)
Same Business Group x ΔImport Price	0.001	0.111	0.022	-0.073**
	(0.043)	(0.076)	(0.053)	(0.030)
ΔExport Price	-0.011	-0.025	0.011	-0.025
	(0.012)	(0.017)	(0.010)	(0.016)
ΔImport Price	0.009	0.025	0.018	-0.009
	(0.013)	(0.018)	(0.014)	(0.015)
Log Avg. Wage Origin	0.201*	0.056	0.462***	-0.091
	(0.119)	(0.150)	(0.107)	(0.180)
Log Avg. Wage Destination	-0.342***	-0.228**	-0.223*	-0.042
	(0.112)	(0.113)	(0.118)	(0.118)
Log Employment Destination	-0.047**	-0.041	-0.016	-0.000
	(0.023)	(0.040)	(0.027)	(0.034)
Log Employment Origin	-0.088	-0.045	-0.087*	-0.123*
	(0.063)	(0.088)	(0.050)	(0.065)
Log Emp. BG Origin	0.808	-0.708	1.795***	-0.137
	(0.818)	(0.946)	(0.675)	(1.003)
Log Emp. BG Dest.	0.720	-0.073	-0.326	3.471***
	(0.805)	(0.817)	(0.988)	(1.238)
Log N. Firms BG Origin	0.245	-0.707	0.279	0.410
	(0.355)	(0.478)	(0.239)	(0.319)
Log N. Firms BG Dest.	0.614***	0.861**	0.424	1.720**
	(0.208)	(0.370)	(0.397)	(0.733)
R^2	0.338	0.354	0.369	0.450
Origin FE	✓	✓	✓	✓
Destination FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Mean DV	.271	.99	-.323	-.453
SD DV	1.245	1.274	.919	.682
N	20188	9184	7523	2459

Notes: The dependent variable is the change in within-firm wage-ranking for the workers that move (movers) between the destination and the origin firm. See Table 3 for the main regression specification and the definition of the variables. Robust standard errors in parentheses are double clustered at the level of the firm of origin and destination of the flow. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: International Trade Shocks and Worker flows within Business Groups

	All Workers	Bot. 25 Workers	Mid. 50 Workers	Top 25 Workers
	(1)	(2)	(3)	(4)
ΔExport Price	0.004*	0.001	0.013*	0.036**
	(0.002)	(0.001)	(0.007)	(0.017)
ΔImport Price	-0.005	-0.005	-0.006	-0.011
	(0.003)	(0.004)	(0.010)	(0.016)
Log Avg. Wage Origin	0.042	0.139**	0.087	0.300
	(0.040)	(0.062)	(0.072)	(0.207)
Log Avg. Wage Destination	-0.139*	-0.064	-0.427***	-0.464**
	(0.074)	(0.039)	(0.147)	(0.186)
Log Employment Origin	-0.053***	-0.165***	-0.055*	-0.124**
	(0.016)	(0.039)	(0.029)	(0.048)
Log Employment Destination	-0.024	-0.031	-0.079**	-0.077***
	(0.017)	(0.021)	(0.038)	(0.022)
Log Emp. Business Group	-0.383	-0.152	-0.223	1.859
	(0.371)	(0.620)	(0.852)	(1.377)
Log N. Firms Business Group	0.063	0.123	-0.249	0.159
	(0.205)	(0.239)	(0.447)	(0.497)
R^2	0.591	0.797	0.647	0.755
Origin FE	✓	✓	✓	✓
Destination FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Mean DV	.051	.08	.096	.188
SD DV	.084	.115	.135	.213
Mean Den. DV	2.1	1.5	1.7	1.6
N	576	255	234	218

Notes: This table reports the results for the OLS regression in Equation (3.2). The sample includes only worker flows within the same business group. See Table 3 for the definition of the variables. Robust standard errors in parentheses are double clustered at the level of the firm of origin and destination of the flow. *** p<0.01, ** p<0.05, * p<0.1.

Table 8: International Trade Shocks and the Extensive Margin of Worker Flows

	All Workers	Bot. 25 Workers	Mid. 50 Workers	Top 25 Workers
	(1)	(2)	(3)	(4)
Same Business Group	5.053***	2.317***	2.579***	2.528***
	(0.694)	(0.445)	(0.481)	(0.373)
Same Business Group x ΔExport Price	0.121	0.373**	-0.207	0.266**
	(0.207)	(0.148)	(0.137)	(0.125)
Same Business Group x ΔImport Price	-0.036	0.089	-0.008	-0.097
	(0.212)	(0.088)	(0.132)	(0.152)
ΔExport Price	0.003	0.001	0.003	-0.000
	(0.005)	(0.003)	(0.003)	(0.002)
ΔImport Price	-0.001	-0.003	0.001	0.001
	(0.003)	(0.002)	(0.002)	(0.001)
Log Avg. Wage Origin	0.155**	0.048**	0.040	0.038
	(0.077)	(0.024)	(0.027)	(0.025)
Log Avg. Wage Destination	0.022	0.002	0.004	-0.005
	(0.024)	(0.011)	(0.014)	(0.006)
Log Employment Destination	0.161***	0.084***	0.070***	0.037***
	(0.026)	(0.015)	(0.013)	(0.007)
Log Employment Origin	0.151***	0.072***	0.056***	0.042***
	(0.022)	(0.013)	(0.009)	(0.006)
Log Emp. Business Group Origin	-0.154	-0.003	-0.091	-0.076*
	(0.198)	(0.132)	(0.089)	(0.045)
Log Emp. Business Group Destination	3.561*	1.566*	1.658*	1.341*
	(1.907)	(0.877)	(0.919)	(0.728)
Log N. Firms Business Group Origin	0.407	0.290*	0.125	0.045
	(0.305)	(0.149)	(0.141)	(0.079)
Log N. Firms Business Group Destination	-2.682**	-1.192**	-1.155*	-0.623
	(1.124)	(0.502)	(0.666)	(0.541)
R^2	0.029	0.016	0.017	0.014
Origin FE	✓	✓	✓	✓
Destination FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Mean DV	.251	.115	.112	.059
SD DV	5.009	3.401	3.349	2.441
Number of observations	4188243	4171227	4186565	4188243

Notes: This table presents evidence for the extensive margin of worker flows between firms. The dependent variable is a dummy equal to one when there is a positive worker flow between two pairs of firms. Because the share of active relationships between firms is small, the dummy is re-scaled from (0, 1) to (0, 100). Sample selection is explained in section 3.6. All origin firms belong to a business group. See Table 3 for other variable definitions. Robust standard errors in parentheses are double clustered at the level of the firm that sends and receives the flow. *** p<0.01, ** p<0.05, * p<0.1.

Table 9: Heterogeneity of Main Results for Top Workers

	Baseline	Tenure	Business Group Tenure	Distance	Push	Same Sector	Sector Integration	Origin Controls Destination	Family Group
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Same Business Group	0.043***	0.028	0.035	0.041**	0.059**	0.012	0.057***	0.022	0.092***
	(0.016)	(0.027)	(0.031)	(0.018)	(0.025)	(0.023)	(0.021)	(0.021)	(0.027)
Same Business Group x ΔExport Price	0.032**	0.038*	0.041**	0.032*	0.061**	0.048***	0.029	0.038**	0.024*
	(0.013)	(0.020)	(0.020)	(0.017)	(0.029)	(0.011)	(0.018)	(0.015)	(0.013)
Same Business Group x ΔExport Price x Z		-0.005	-0.007	0.007	-0.052*	-0.029	0.029	0.542***	0.008
		(0.015)	(0.014)	(0.086)	(0.030)	(0.022)	(0.075)	(0.128)	(0.021)
ΔExport Price	0.006	0.011	0.011	0.008	0.006	0.005	0.004	0.007	0.006
	(0.004)	(0.008)	(0.008)	(0.005)	(0.007)	(0.005)	(0.005)	(0.004)	(0.004)
R^2	0.697	0.698	0.698	0.698	0.699	0.699	0.699	0.712	0.698
Origin FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Destination FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Baseline controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mean DV	.122	.122	.122	.122	.122	.122	.122	.122	.122
SD DV	.16	.16	.16	.16	.16	.16	.16	.16	.16
Mean Den. DV	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1	1.1
N	2459	2459	2459	2459	2459	2459	2459	2459	2459

Notes: This table shows results when adding triple interactions of the same-group dummy, export shocks, and proxies for several frictions (Z). The variables used for the triple interactions are Tenure (tenure of the worker in the origin firm), Business Group Tenure (tenure of the worker in the business group of the origin firm), Distance (geodesic distance between the origin and destination), Push (whether the shock at the origin firm is negative), Same Sector (a dummy for whether the firms are in the same sector), Sector integration (measured from the input-output matrix of the Chilean economy), Origin Controls Destination (a dummy that takes the value one if the origin firms has an ownership stake greater than 50% of the destination firm). The sample includes only workers in the top quartile of the within-firm wage distribution of the firm of origin. See Table 3 for the main regression specification and the definition of the variables. All columns include the baseline controls from Table 3. Robust standard errors in parentheses are double clustered at the level of the firm of origin and destination of the flow. *** p<0.01, ** p<0.05, * p<0.1.

Table 10: Average Effect of Receiving a Top Worker from Within the Same Business Group

	(1) Net exports over wage bill	(2) Net exports over employment	(3) Average wage	(4) Stayers average wage
	Panel A (Figure 3)	Panel B (Figure 3)	Panel C (Figure 3)	Panel D (Figure 3)
Number of treated units	92	92	92	92
Potential controls	2,985	2,985	2,985	2,985
Average effect	0.453	1340.1	0.123	0.094
CI 99%	[-0.003, 0.0001]	[-28.3, 0.227]	[-0.006, 0.002]	[-0.001, 0.070]
CI 95%	[-0.003, 0.0001]	[-28.3, 0.227]	[-0.002, 0.001]	[-0.000, 0.007]

Notes: This table presents average effects on net exports (exports minus imports) and log average wages for treated firms against synthetic controls. Treated firms are group firms that receive a top worker from within the same business group. Control firms are group or standalone firms that receive a top worker from an unaffiliated firm. The average effect is computed as the average cumulative difference between the treated firms and the synthetic controls for years 0 through 3. Columns (1) presents the treatment effect for net exports over the firm's wage bill, Column (2) for net exports over the firm's number of employees, Column (3) for the average wage of all workers, and Column (4) for the average wage of workers that worked at the firm before the arrival of the new top worker. In square brackets we present confidence intervals (CI) at the 1% and 5% levels. Confidence intervals are based on placebo treatment groups in 100 random samples. The choice of synthetic controls is discussed in Section 5.

Online Appendix

Table A.1: Summary Statistics for International Trade Shocks

	Mean		SD	
	Exports	Imports	Exports	Imports
Standalone	0.033	0.019	0.628	0.363
Business Group	0.027	0.021	0.851	0.265

Notes: This table presents statistics for export and import price shocks. It presents the mean and standard deviations of export and import shocks for standalone firms and firms affiliated to business groups.

Table A.2: Exposure to International Trade (%)

		Firms	Employment	Wage Bill
Business Group Firms	Exports	43	53	56
	Imports	68	75	83
Standalone Firms	Exports	14	24	32
	Imports	33	55	64

Notes: This table presents the share of firms (first column), the share of employment (second column) and the share of wage bill (third column) that is exposed to international trade, both in terms of export and import activity. It documents this for business group firms (Row 1-2) and standalone firms (Row 3-4). Note that we use the set of standalone firms that are used in the main regressions. This implies that these standalone firms have worker flows with business group firms.

Table A.3: Worker Flows Between Same-Group Firms and Unaffiliated Firms

	All Workers			Top Workers		
	Same BG	Unaffiliated	Difference P-value	Same BG	Unaffiliated	Difference P-value
	(1)	(2)	(3)	(4)	(5)	(6)
Outflows	0.053	0.019	0.034***	0.198	0.115	0.082***
	(0.004)	(0.000)	[0.000]	(0.014)	(0.002)	[0.000]
Inflows	0.043	0.018	0.026***	0.125	0.075	0.050***
	(0.003)	(0.000)	[0.000]	(0.010)	(0.001)	[0.000]

Notes: This table shows the average of worker outflows and inflows between pairs of same-business-group (BG) firms and unaffiliated firms. Outflows (inflows) are defined as the number of workers sent by the origin firm to the destination firm normalized by the total number of workers sent (hired) by the origin (destination) firm in a year. Columns 1 to 3 present the average flows for the full sample of workers, while columns 4 to 6 show the average flows only for top workers (top quartile of the within-firm wage distribution of the firm of origin). Standard errors are presented in parenthesis, while P-values in brackets.

Table A.4: Trade Shocks and Internal Labor Markets: Adding Lagged Shocks

	All Workers	Bot. 25 Workers	Mid. 50 Workers	Top 25 Workers	Top 20 Workers	Top 10 Workers
	(1)	(2)	(3)	(4)	(5)	(6)
Same Business Group	0.022***	0.017***	0.024**	0.043**	0.052**	0.023
	(0.005)	(0.006)	(0.010)	(0.017)	(0.024)	(0.032)
Same Business Group x ΔExport Price	0.003*	-0.001	0.007	0.039***	0.032**	0.077**
	(0.002)	(0.002)	(0.005)	(0.015)	(0.015)	(0.030)
Same Business Group x Δ_{-1}Export Price	-0.006	-0.009	-0.025	0.122	0.110	-0.005
	(0.011)	(0.020)	(0.031)	(0.083)	(0.088)	(0.132)
Same Business Group x ΔImport Price	-0.004	-0.012*	-0.015*	-0.010	-0.002	0.008
	(0.004)	(0.007)	(0.009)	(0.011)	(0.012)	(0.025)
Same Business Group x Δ_{-1}Import Price	-0.001	-0.098	-0.050	-0.050	-0.025	0.049
	(0.025)	(0.086)	(0.077)	(0.064)	(0.082)	(0.153)
ΔExport Price	0.001	0.001	0.002	0.007*	0.001	-0.017
	(0.001)	(0.001)	(0.002)	(0.004)	(0.005)	(0.013)
Δ_{-1}Export Price	0.002	0.002	0.004	0.031	0.010	0.017
	(0.003)	(0.005)	(0.010)	(0.025)	(0.031)	(0.059)
ΔImport Price	-0.001	0.001	-0.001	-0.003	-0.005	-0.006
	(0.001)	(0.001)	(0.002)	(0.002)	(0.004)	(0.007)
Δ_{-1}Import Price	-0.004	-0.010	0.002	-0.019	-0.023	-0.106
	(0.004)	(0.008)	(0.011)	(0.034)	(0.050)	(0.078)
Log Avg. Wage Origin	0.003	0.016	-0.013	0.044	0.050	0.279**
	(0.018)	(0.017)	(0.017)	(0.079)	(0.078)	(0.121)
Log Avg. Wage Destination	0.000	-0.001	-0.002	-0.057	-0.068	-0.071
	(0.003)	(0.005)	(0.008)	(0.038)	(0.047)	(0.090)
Log Employment Destination	-0.002*	-0.004**	-0.006*	-0.022**	-0.028**	-0.048**
	(0.001)	(0.002)	(0.003)	(0.010)	(0.012)	(0.021)
Log Employment Origin	-0.046***	-0.086***	-0.074***	-0.161***	-0.193***	-0.252***
	(0.009)	(0.017)	(0.013)	(0.030)	(0.030)	(0.041)
Log Emp. Business Group Origin	-0.081	-0.276	-0.146	0.307	0.264	0.456
	(0.079)	(0.176)	(0.249)	(0.328)	(0.427)	(0.584)
Log Emp. Business Group Dest.	-0.119**	-0.278***	-0.134	-0.261	-0.028	0.563
	(0.049)	(0.096)	(0.141)	(0.203)	(0.305)	(0.772)
Log N. Firms Business Group Origin	0.067*	0.097*	0.081**	0.375**	0.398**	0.407
	(0.037)	(0.055)	(0.039)	(0.167)	(0.181)	(0.284)
Log N. Firms Business Group Dest.	0.013	0.018	0.031	-0.035	-0.031	0.651
	(0.016)	(0.020)	(0.031)	(0.170)	(0.227)	(1.137)
R^2	0.595	0.681	0.639	0.700	0.689	0.748
Origin FE	✓	✓	✓	✓	✓	✓
Destination FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Sector-Yr FE						
Mean DV	.02	.037	.047	.122	.144	.233
SD DV	.042	.066	.084	.16	.181	.251
Mean Den. DV	1.2	1.2	1.3	1.1	1.1	1.1
N	20188	9184	7523	2459	1976	923

Notes: This table presents evidence of the analysis implemented in Table 3 but adding dynamic interaction of trade shocks. For more details on the specification and variables included as controls, go to Table 3.

Table A.5: Persistence of Worker Outflows: Serial Correlations at Pair-Level

	Intensive Margin	Extensive Margin
Autocorrelation t and $t-1$	0.077***	0.012***
	(0.000)	(0.000)
R^2	0.790	0.077
N	1,660,221	64,872,264

Notes: This table documents the autocorrelation of worker flows between firms. It shows it in the intensive margin: number of workers that flow between a pair of firms over time. And it shows it for the extensive margin as well: whether two firms have worker flows or not. *** p<0.01, ** p<0.05, * p<0.1.

Table A.6: Trade Shocks and Wage Changes: Heterogeneity Analysis

	Wage Change			Wage Rank Change		
	(1) Baseline	(2) Tenure	(3) Origin Controls Destination	(4) Baseline	(5) Tenure	(6) Origin Controls Destination
Same Business Group	0.085*	0.046	0.083*	0.039	0.093	-0.031
	(0.048)	(0.071)	(0.049)	(0.066)	(0.104)	(0.072)
Same Business Group x ΔPrice Exports	0.066***	0.067*	0.067***	0.090**	0.071	0.099*
	(0.022)	(0.034)	(0.022)	(0.043)	(0.058)	(0.050)
Same Business Group x ΔExport Price x Z		-0.003	0.030		0.011	0.296
		(0.026)	(0.095)		(0.048)	(0.216)
ΔPrice Exports	-0.009	-0.009	-0.009	-0.025	-0.064***	-0.025
	(0.008)	(0.011)	(0.008)	(0.016)	(0.022)	(0.016)
Log Avg. Wage Origin	-0.449***	-0.444***	-0.448***	-0.091	-0.139	-0.103
	(0.056)	(0.055)	(0.056)	(0.180)	(0.180)	(0.178)
Log Avg. Wage Destination	0.072	0.069	0.070	-0.042	-0.035	-0.057
	(0.083)	(0.083)	(0.084)	(0.118)	(0.119)	(0.121)
Log Employment Destination	-0.008	-0.008	-0.008	-0.000	-0.002	0.002
	(0.026)	(0.026)	(0.026)	(0.034)	(0.034)	(0.036)
Log Employment Origin	-0.055**	-0.059**	-0.055**	-0.123*	-0.137**	-0.127*
	(0.024)	(0.024)	(0.024)	(0.065)	(0.065)	(0.065)
Log Emp. Business Group Origin	-0.652	-0.838	-0.601	-0.137	-0.186	-0.114
	(0.627)	(0.681)	(0.665)	(1.003)	(1.026)	(1.011)
Log Emp. Business Group Dest.	-0.620	-0.613	-0.645	3.471***	3.494**	3.632***
	(0.499)	(0.513)	(0.495)	(1.238)	(1.410)	(1.242)
Log N. Firms Business Group Origin	-0.066	0.006	-0.048	0.410	0.435	0.401
	(0.360)	(0.351)	(0.366)	(0.319)	(0.317)	(0.319)
Log N. Firms Business Group Dest.	0.366	0.385	0.369	1.720**	1.671**	1.604**
	(0.429)	(0.426)	(0.431)	(0.733)	(0.754)	(0.737)
R^2	0.524	0.526	0.525	0.450	0.452	0.451
Origin FE	✓	✓	✓	✓	✓	✓
Destination FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Mean DV	.134	.134	.134	-.453	-.453	-.453
SD DV	.356	.356	.356	.682	.682	.682
N	2606	2606	2606	2459	2459	2459

Notes: This table shows results when adding triple interactions of the same-group dummy, export shocks, and proxies for several frictions (Z) when the outcome is wage change of movers (Columns 1-3) and wage rank change of movers (Columns 4-6). The variables used for the triple interactions are Tenure (tenure of the worker in the origin firm) and Origin Controls Destination (a dummy that takes the value one if the origin firms has an ownership stake greater than 50% of the destination firm). The sample includes only workers in the top quartile of the within-firm wage distribution of the firm of origin. See Table 3 for the main regression specification and the definition of the variables. All columns include the baseline controls from Table 3. Robust standard errors in parentheses are double clustered at the level of the firm of origin and destination of the flow. *** p<0.01, ** p<0.05, * p<0.1.

Table A.7: Heterogeneity of Internal Labor Flows to Pull and Push Shocks

	All Workers		Bot. 25 Workers		Mid. 50 Workers		Top 25 Workers	
	(1) Push	(2) Pull	(3) Push	(4) Pull	(5) Push	(6) Pull	(7) Push	(8) Pull
Same Business Group	0.023***	0.018***	0.022**	0.016**	0.028**	0.018	0.059**	0.022
	(0.007)	(0.006)	(0.009)	(0.007)	(0.013)	(0.013)	(0.025)	(0.017)
Same Business Group x ΔExport Price	0.005*	0.005	0.001	0.001	0.011*	0.009	0.061**	0.028**
	(0.003)	(0.004)	(0.004)	(0.005)	(0.006)	(0.006)	(0.029)	(0.012)
Same Business Group x ΔExport Price x Z	-0.003	-0.006	0.002	-0.003	-0.006	-0.006	-0.052*	0.001
	(0.005)	(0.005)	(0.005)	(0.007)	(0.008)	(0.009)	(0.030)	(0.021)
ΔExport Price	0.000	0.001	0.001	0.001	0.001	0.001	0.006	0.006
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.007)	(0.005)
Log Employment Destination	-0.002*	-0.002*	-0.004**	-0.004**	-0.006*	-0.006*	-0.022**	-0.023**
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)	(0.010)	(0.011)
Log Employment Origin	-0.046***	-0.046***	-0.086***	-0.086***	-0.074***	-0.073***	-0.160***	-0.158***
	(0.009)	(0.009)	(0.017)	(0.017)	(0.012)	(0.012)	(0.031)	(0.030)
Log Emp. Business Group Origin	-0.086	-0.083	-0.288	-0.282	-0.151	-0.155	0.354	0.306
	(0.079)	(0.079)	(0.175)	(0.174)	(0.249)	(0.248)	(0.342)	(0.327)
Log Emp. Business Group Dest.	-0.114**	-0.111**	-0.254**	-0.254**	-0.135	-0.117	-0.192	-0.177
	(0.049)	(0.052)	(0.097)	(0.102)	(0.140)	(0.151)	(0.226)	(0.222)
Log N. Firms Business Group Origin	0.069*	0.068*	0.098*	0.099*	0.084**	0.080**	0.394**	0.387**
	(0.036)	(0.037)	(0.055)	(0.056)	(0.039)	(0.038)	(0.162)	(0.168)
Log N. Firms Business Group Dest.	0.013	0.012	0.017	0.016	0.029	0.028	-0.022	-0.063
	(0.015)	(0.015)	(0.021)	(0.020)	(0.031)	(0.031)	(0.167)	(0.160)
R^2	0.595	0.595	0.681	0.681	0.639	0.640	0.699	0.698
Origin FE	✓	✓	✓	✓	✓	✓	✓	✓
Destination FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Mean DV	.02	.02	.037	.037	.047	.047	.122	.122
SD DV	.042	.042	.066	.066	.084	.084	.16	.16
Mean Den. DV	1.2	1.2	1.2	1.2	1.3	1.3	1.1	1.1
N	20188	20188	9184	9184	7523	7523	2459	2459

Notes: This table shows results when adding triple interactions of the same-group dummy, export shocks, and proxies for several frictions (Z). The variables used for the triple interactions are Push (whether the shock at the origin firm is negative) and Pull (whether the shock at the destination firm is positive). The sample includes only workers in the top quartile of the within-firm wage distribution of the firm of origin. See Table 3 for the main regression specification and the definition of the variables. All columns include the baseline controls from Table 3. Robust standard errors in parentheses are double clustered at the level of the firm of origin and destination of the flow. *** p<0.01, ** p<0.05, * p<0.1.

Table A.8: Heterogeneity of Internal Labor Flows to Pull and Push Shocks: Wage Changes

	All Workers		Bot. 25		Mid. 50		Top 25	
	(1) Push	(2) Pull	(3) Push	(4) Pull	(5) Push	(6) Pull	(7) Push	(8) Pull
Same Business Group	-0.014	0.022	-0.037	0.022	-0.009	0.025	0.090*	0.132**
	(0.023)	(0.028)	(0.038)	(0.046)	(0.041)	(0.053)	(0.051)	(0.052)
Same Business Group x ΔPrice Exports	0.005	0.023*	-0.010	0.004	-0.001	0.021	0.075***	0.118***
	(0.009)	(0.014)	(0.013)	(0.017)	(0.013)	(0.026)	(0.023)	(0.037)
Same Business Group x ΔExport Price x Z	-0.034*	-0.038	-0.012	-0.013	0.010	-0.026	-0.034	-0.068
	(0.020)	(0.024)	(0.032)	(0.037)	(0.026)	(0.029)	(0.054)	(0.048)
ΔPrice Exports	-0.001	-0.010*	0.004	-0.006	-0.001	-0.007	-0.009	-0.027*
	(0.003)	(0.006)	(0.005)	(0.008)	(0.006)	(0.011)	(0.008)	(0.016)
Log Avg. Wage Origin	-0.432***	-0.431***	-0.612***	-0.612***	-0.542***	-0.539***	-0.448***	-0.448***
	(0.033)	(0.033)	(0.044)	(0.044)	(0.047)	(0.047)	(0.056)	(0.057)
Log Avg. Wage Destination	0.100**	0.102**	0.039	0.041	0.062	0.064	0.075	0.066
	(0.041)	(0.040)	(0.036)	(0.037)	(0.043)	(0.044)	(0.083)	(0.085)
Log Employment Destination	-0.011	-0.009	-0.050**	-0.048**	-0.014	-0.014	-0.009	-0.005
	(0.016)	(0.016)	(0.021)	(0.021)	(0.018)	(0.017)	(0.026)	(0.024)
Log Employment Origin	-0.057***	-0.056***	-0.036**	-0.035**	-0.045***	-0.044***	-0.055**	-0.055**
	(0.008)	(0.008)	(0.014)	(0.014)	(0.011)	(0.011)	(0.025)	(0.024)
Log Emp. Business Group Origin	0.200	0.200	0.006	-0.037	0.399	0.445	-0.583	-0.704
	(0.339)	(0.338)	(0.402)	(0.395)	(0.456)	(0.448)	(0.649)	(0.610)
Log Emp. Business Group Dest.	0.085	0.089	0.384	0.373	0.255	0.281	-0.595	-0.619
	(0.335)	(0.340)	(0.386)	(0.393)	(0.420)	(0.424)	(0.486)	(0.492)
Log N. Firms Business Group Origin	-0.008	-0.005	-0.054	-0.049	-0.119	-0.137	-0.126	-0.013
	(0.186)	(0.188)	(0.145)	(0.153)	(0.187)	(0.184)	(0.376)	(0.365)
Log N. Firms Business Group Dest.	0.185	0.206	0.158	0.177	0.267	0.275	0.367	0.404
	(0.191)	(0.195)	(0.203)	(0.211)	(0.214)	(0.219)	(0.438)	(0.431)
R^2	0.465	0.465	0.528	0.528	0.567	0.567	0.525	0.525
Origin FE	✓	✓	✓	✓	✓	✓	✓	✓
Destination FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Mean DV	.2	.2	.243	.243	.175	.175	.134	.134
SD DV	.411	.411	.428	.428	.404	.404	.356	.356
N	20012	20012	7389	7389	9273	9273	2606	2606

Notes: This table shows results when adding triple interactions of the same-group dummy, export shocks, and proxies for several frictions (Z) when the outcome is wage changes of workers who move between firms. The variables used for the triple interactions are Push (whether the shock at the origin firm is negative) and Pull (whether the shock at the destination firm is positive). The sample includes only workers in the top quartile of the within-firm wage distribution of the firm of origin. See Table 3 for the main regression specification and the definition of the variables. All columns include the baseline controls from Table 3. For reference, this regression is the same specification as in Table A.7 but when the outcome is wage changes of movers rather than worker flows. Robust standard errors in parentheses are double clustered at the level of the firm of origin and destination of the flow. *** p<0.01, ** p<0.05, * p<0.1.

Table A.9: Firm-Level Regressions with Export Shocks

	ΔLog. Wages(t)				ΔLog. Employment(t)	ΔROA(t)	ΔROE(t)	Churn(t)	Fired(t)	Hired(t)
	(1) All	(2) Bot. 25	(3) Mid. 50	(4) Top 25	(5)	(6)	(7)	(8)	(9)	(10)
ΔExport(t) x BG	0.003	0.008	0.001	0.003	-0.020	0.050	0.209	0.009	-0.004	0.014
	(0.011)	(0.010)	(0.015)	(0.014)	(0.033)	(0.032)	(0.146)	(0.019)	(0.012)	(0.013)
ΔExport(t-1) x BG	0.035***	0.040***	0.035***	0.032***	-0.098***	0.016	0.257*	-0.035*	-0.010	-0.026*
	(0.005)	(0.014)	(0.006)	(0.009)	(0.021)	(0.038)	(0.148)	(0.018)	(0.009)	(0.013)
ΔExport(t-2) x BG	0.021**	-0.001	0.025**	0.025**	-0.101***	0.146**	0.568	-0.046***	-0.014	-0.032***
	(0.009)	(0.019)	(0.010)	(0.011)	(0.037)	(0.067)	(0.362)	(0.016)	(0.011)	(0.011)
ΔExport(t-3) x BG	0.016*	0.016	0.011	0.020***	-0.081**			-0.038***	-0.008	-0.030***
	(0.009)	(0.014)	(0.011)	(0.007)	(0.031)			(0.008)	(0.009)	(0.008)
ΔExport(t)	-0.002	-0.002	-0.002	-0.001	0.004	-0.055*	-0.238	-0.003	-0.002	-0.001
	(0.003)	(0.005)	(0.003)	(0.004)	(0.006)	(0.030)	(0.143)	(0.004)	(0.003)	(0.002)
ΔExport(t-1)	-0.008***	-0.006	-0.008***	-0.007*	0.017**	-0.003	-0.205	0.009**	0.003	0.006*
	(0.003)	(0.004)	(0.003)	(0.004)	(0.007)	(0.027)	(0.132)	(0.004)	(0.003)	(0.003)
ΔExport(t-2)	-0.013***	-0.011*	-0.013***	-0.013**	0.024	-0.169**	-0.594	0.011*	0.001	0.010*
	(0.005)	(0.006)	(0.005)	(0.006)	(0.018)	(0.061)	(0.367)	(0.007)	(0.002)	(0.006)
ΔExport(t-3)	-0.007*	-0.005	-0.005*	-0.008**	0.012			0.005	-0.001	0.005
	(0.003)	(0.006)	(0.003)	(0.004)	(0.009)			(0.004)	(0.003)	(0.004)
R^2	0.175	0.105	0.148	0.178	0.258	0.287	0.236	0.564	0.485	0.452
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mean DV	.035	.026	.036	.039	.067	-.006	-.004	.528	.248	.279
SD DV	.117	.219	.149	.129	.305	.073	.286	.229	.158	.135
N	6343	6343	6343	6343	6343	148	148	6343	6343	6343

Notes: This table reports firm-level panel regressions for annual log change in wages of workers in different segments of the wage distribution (All, Bottom 25, Middle 50, Top 25), log change in total employment, changes in return-on-assets (ROA), return-on-equity (ROE), gross churning of workers, share of workers fired and share of workers hired. ROA and ROE are only available for listed firms. Export price shocks are annual log differences in global export prices for each firm (see section 2). BG is a dummy for those firms that are part of a business group. Robust standard errors in parentheses are clustered at the firm level. *** p<0.01, ** p<0.05, * p<0.1.

Table A.10: Average Effect of Receiving a Top Worker from Within the Same Business Group: Using Nearest-Neighbor Matching

	(1) Net exports over wage bill	(2) Net exports over employment	(3) Average wage	(4) Stayers average wage
Treatment effect	1.258**	27985.4*	0.154***	0.153***
	(0.627)	(15778.9)	(0.049)	(0.049)
Number of treated units	92	92	92	92
Potential controls	2,985	2,985	2,985	2,985

Notes: This table presents average effects on net exports (exports minus imports) and log average wages for treated firms using nearest-neighbor matching based on the Mahalanobis metric following Abadie, Drukker, Herr, and Imbens (2004). Treated firms are group firms that receive a top worker from within the same business group. Control firms are group or standalone firms that receive a top worker from an unaffiliated firm. Columns (1) presents the treatment effect for net exports over the firm's wage bill, Column (2) for net exports over the firm's number of employees, Column (3) for the average wage of all workers, and Column (4) for the average wage of workers that worked at the firm before the arrival of the new top worker. Heteroskedastic-robust variance estimator presented in parenthesis following Abadie and Imbens (2006). *** p<0.01, ** p<0.05, * p<0.1.

Table A.11: Heterogeneous Effects of Receiving a Top Worker from Within the Same Business Group

	(1) Net exports over wage bill	(2) Net exports over employment	(3) Average wage	(4) Stayers average wage
Origin controls destination	0.115	5706	0.146	0.198
Push shock	12.46	201758.1	0.088	0.206
CI 99%	[-0.003, 0.0001]	[-28.3, 0.227]	[-0.006, 0.002]	[-0.001, 0.070]
CI 95%	[-0.003, 0.0001]	[-28.3, 0.227]	[-0.002, 0.001]	[-0.000, 0.007]

Notes: This table presents average effects on net exports (exports minus imports) and log average wages for treated firms against synthetic controls. Treated firms are group firms that receive a top worker from within the same business group. Control firms are group or standalone firms that receive a top worker from an unaffiliated firm. The average effect is computed as the average cumulative difference between the treated firms and the synthetic controls for years 0 through 3. We compute this average for two subgroups of treated firms. *Origin controls destination* shows the average for the case where the firm receive a top worker from a firm that has an ownership stake greater than 50% of the destination firm. *Push shock* shows the average for the case where the firm receive a top worker and the shock at the origin firm is negative. Columns (1) presents the treatment effect for net exports over the firm's wage bill, Column (2) for net exports over the firm's number of employees, Column (3) for the average wage of all workers, and Column (4) for the average wage of workers that worked at the firm before the arrival of the new top worker. In square brackets we present confidence intervals (CI) at the 1% and 5% levels. Confidence intervals are based on placebo treatment groups in 100 random samples. The choice of synthetic controls is discussed in Section 5.

Table A.12: Internal Labor Reallocation using Shocks to Industry-Level Tobin's Q

	All Workers		Bottom 25 Workers		Middle 50 Workers		Top 25 Workers	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Same Business Group	0.039***		0.032***		0.051***		0.058***	
	(0.005)		(0.007)		(0.008)		(0.015)	
Same Business Group x ΔQ	0.008	0.009	0.011*	0.012	0.007	0.004	0.024**	0.022**
	(0.006)	(0.007)	(0.006)	(0.008)	(0.006)	(0.007)	(0.011)	(0.009)
ΔQ	0.000	-0.000	0.001	0.001	0.000	0.000	0.002	0.002
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.002)	(0.002)
Log Avg. Wage Origin	0.053***	0.037**	0.028*	0.001	0.042*	0.025	0.094**	0.116
	(0.014)	(0.014)	(0.015)	(0.010)	(0.021)	(0.022)	(0.037)	(0.067)
Log Avg. Wage Destination	-0.001	-0.003	-0.006	-0.014	-0.005	-0.011	-0.032*	-0.064**
	(0.003)	(0.005)	(0.005)	(0.009)	(0.005)	(0.011)	(0.018)	(0.026)
Log Employment Destination	-0.002***	-0.004**	-0.005**	-0.005*	-0.007***	-0.008**	-0.015***	-0.023**
	(0.001)	(0.001)	(0.002)	(0.003)	(0.002)	(0.003)	(0.005)	(0.008)
Log Employment Origin	-0.052***	-0.035***	-0.098***	-0.073***	-0.088***	-0.061***	-0.143***	-0.115***
	(0.006)	(0.004)	(0.011)	(0.015)	(0.010)	(0.009)	(0.014)	(0.016)
Log Emp. Business Group Origin	0.030	0.041	-0.049	0.046	0.133**	0.115	0.369**	0.657***
	(0.042)	(0.022)	(0.146)	(0.141)	(0.056)	(0.068)	(0.175)	(0.172)
Log Emp. Business Group Dest.	-0.170***	-0.168**	-0.128	-0.198	-0.212**	-0.254	-0.332	-0.304
	(0.055)	(0.058)	(0.095)	(0.150)	(0.098)	(0.154)	(0.221)	(0.317)
Log N. Firms Business Group Origin	0.028	0.017	0.051	0.031	0.031	0.033	0.003	-0.053
	(0.027)	(0.011)	(0.063)	(0.028)	(0.038)	(0.035)	(0.097)	(0.076)
Log N. Firms Business Group Dest.	0.027	0.063	0.058*	0.094	0.004	-0.000	-0.133	0.085
	(0.027)	(0.038)	(0.030)	(0.066)	(0.041)	(0.067)	(0.199)	(0.229)
R^2	0.666	0.743	0.746	0.804	0.712	0.765	0.755	0.814
Pair FE		✓		✓		✓		✓
Origin FE	✓		✓		✓		✓	
Destination FE	✓		✓		✓		✓	
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Mean DV	.028	.025	.047	.037	.058	.049	.136	.124
SD DV	.075	.07	.107	.091	.127	.119	.205	.2
Mean Den. DV	1.3	2	1.2	1.5	1.5	2	1.3	1.6
N	50593	24042	22817	9712	21161	9622	7436	3023

Notes: See Table 3 for the main regression specification and the definition of the variables. Δ Q is defined as the difference in Tobin's Q growth between the destination and origin industries. Tobin's Q is defined as the ratio between the market and book value of assets at the industry-level of listed firms. Robust standard errors in parentheses are double clustered at the level of the firm of origin and destination of the flow. *** p<0.01, ** p<0.05, * p<0.1.