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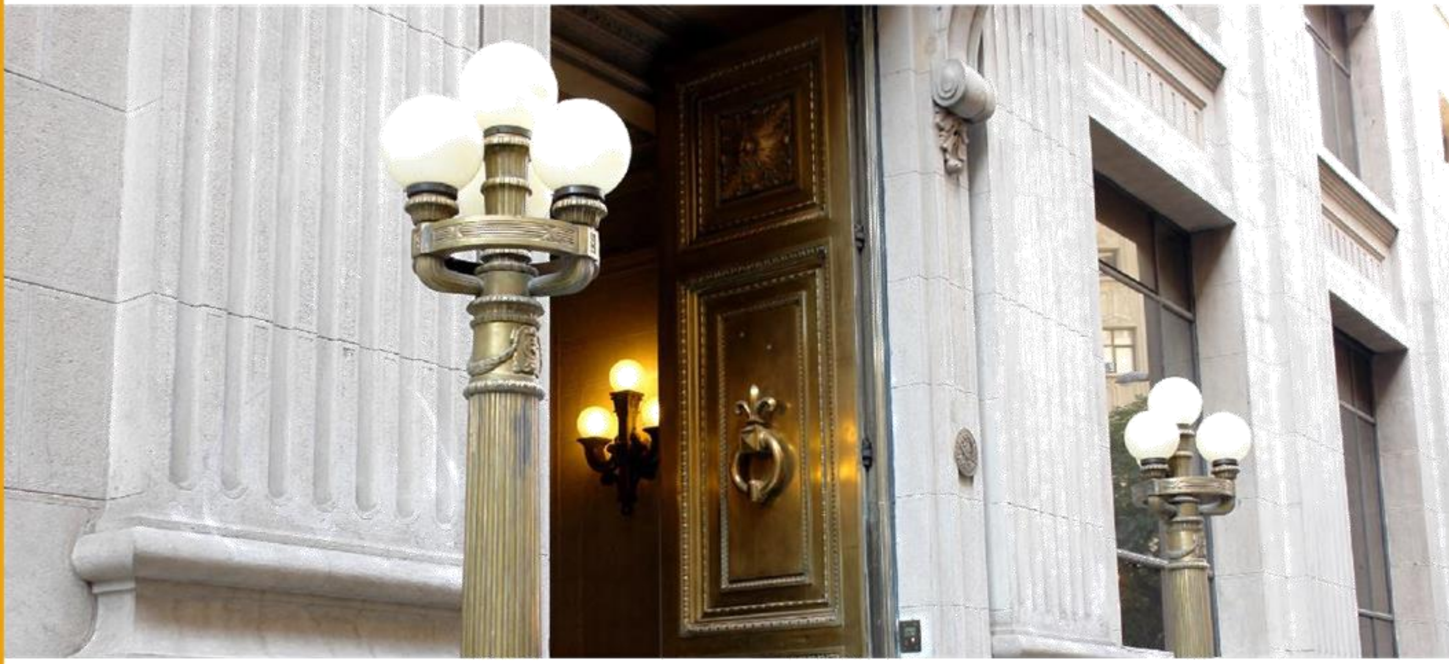

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Ownership Networks and Earnings Inequality*

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Abstract

We use matched employer-employee data together with data on the ownership networks of Chilean firms to document a novel relationship between inequality in labor income and ownership structures. Exploiting transitions of firms in and out of networks, we show that network afiliation is associated with higher inequality along two dimensions. First, network firms pay higher average wages than stand-alone firms, increasing between-firm inequality. Second, the dispersion of wages within a network firm is higher than within a stand-alone firm, increasing within-firm inequality. The effects are driven by increases in the wages of top workers, and by the entry of new top workers. Our findings shed light on the relationship between ownership structures and the distribution of labor income in the economy.

Resumen

Utilizamos datos emparejados entre empleador y empleado junto con datos sobre las redes de propiedad de las empresas chilenas para documentar una nueva relación entre la desigualdad de los ingresos laborales y las estructuras de propiedad. Explotando las transiciones de las empresas dentro y fuera de las redes de propiedad, mostramos que pertenecer a la red está asociado a una mayor desigualdad en dos dimensiones. En primer lugar, las empresas de la red pagan salarios promedios más altos que las empresas independientes, lo que aumenta la desigualdad entre empresas. En segundo lugar, la dispersión de los salarios dentro de una empresa de la red es mayor que dentro de una empresa independiente, lo que aumenta la desigualdad dentro de la empresa. Los efectos se deben al aumento de los salarios de los trabajadores mejor pagados y a la entrada de nuevos trabajadores mejor pagados. Nuestros resultados aportan sobre la relación entre las estructuras de propiedad y la distribución de los ingresos laborales en la economía.

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1 Introduction

The global financial crisis has put earnings inequality once again at the center stage of discussions among economists and policymakers. Financial regulators and investors have recently joined the debate by expressing concerns about high inequality within firms.[1] Academics have also started to explore the contribution of firms to a country's earnings inequality (Song, Price, Guvenen, Bloom, and von Wachter, 2018; Mueller, Ouimet, and Simintzi, 2017a,b). With the use of matched employer-employee datasets, these papers have been able to decompose overall inequality into two components related to firms: dispersion in average earnings across firms and within-firm dispersion of earnings across workers.

In this paper, we use a matched employer-employee dataset to study the relationship between earnings inequality and the ownership structure of firms. There is evidence that ownership structures have an impact on firm value, financing policies, investment, productivity, and other firm-level outcomes. For instance, there is a vast literature on conglomerates where different divisions, often unrelated in terms of production, are linked through ownership (e.g., see Stein (2003) for investment within conglomerates). Given this evidence it is natural to relate ownership structures and worker wages. Ownership refers to the organization of capital, and this can have an impact on the productivity of workers, the skills that are selected in different ownership structures, or the rents that are shared between owners and workers. In this paper we focus on business groups, which are common corporate structures around the world (Khanna and Yafeh, 2007). Business groups form networks of firms related to a single ultimate owner. We find a relationship between business-group affiliation and earnings inequality in those firms. Hence, our paper connects the distribution of control over real assets to the distribution of wages in the economy.

Our data is from Chile, which is a country with a high level of inequality, in fact one of the highest among OECD countries (OECD, 2016). At the same time, business groups are prevalent in Chile (Buchuk, Larrain, Munoz, and Urzúa, 2014; Aldunate, González, Prem, Urzúa, et al., 2020). As an example, Figure 1 shows the corporate structure of Antarchile, one of the largest business groups in Chile. We document that business groups contribute to earnings inequality by paying higher average wages than stand-alone firms and by having higher within-firm earnings dispersion.

Following Song, Price, Guvenen, Bloom, and von Wachter (2018), we start by decom-

[1] For the first time, a new Securities and Exchange Commission rule mandated under the 2010 Dodd-Frank act requires publicly traded firms to disclose the ratio the firm's CEO earnings and the firm's median worker earnings.

posing overall dispersion of earnings in Chile into a between-firm and within-firm component. The between-firm component reflects the dispersion of average firm-level earnings across firms. The within-firm component reflects the dispersion of earnings across workers inside each firm. Overall earnings inequality has remained essentially flat during our sample period 2004-2016 (see Figure 2). The within-firm component contributes slightly more than the between-firm component to overall inequality. However, the relative importance of both components has remained basically unchanged during this period.

We study the role of business groups in contributing to overall earnings inequality by studying the connection between business group affiliation and the between-firm and within-firm components of inequality. To study how business groups contribute to overall earnings inequality through the between-firm component, we start by comparing average earnings of group firms and stand-alone firms. We find that the average wages paid by group firms are substantially higher than those paid by stand-alone firms (Figure 3). Next, we regress average firm earnings into a business group indicator variable, after controlling for observable firm characteristics such as size (number of workers), worker composition (share of female workers, average age of workers, average tenure of workers), and industry-year fixed effects. Regressions confirm that group firms pay on average 36% higher wages than stand-alone firms. This is a novel finding that we label the 'group premium'. We document a significant 'group premium' in all segments of the earnings distribution, indicating that this premium is not driven exclusively by the very top-earnings workers.

We then compare the within-firm earnings dispersion of group firms and stand-alone firms. Controlling for firm size, observable worker composition, and industry-year fixed effects, we find that the standard deviation of earnings inside group firms is roughly 5% higher than in stand-alone firms. This difference explains 30% of the variation in within-firm dispersion. We regress the relative earnings of different segments of the earnings distribution on the business group indicator. We observe the largest effect of group affiliation for the relative earnings between the top 10th percentile and the bottom 10th percentile of workers. We also find significant effects when comparing earnings at the top 50th percentile with the bottom 10th percentile of the distribution. This means that the within-firm differences are not driven solely by the very top workers.

The empirical strategy used in the previous tests exploits between-firm variation: we compare average earnings and earnings dispersion of a business-group firm and a stand-alone firm controlling for year and sector effects, firm size, and worker composition. Although we control for observable firm characteristics, our results could be explained by unobservable firm characteristics that correlate with group affiliation and lead to higher earnings. For example, perhaps group firms operate in market segments that require high-productivity workers (e.g., export firms). These workers would have earned higher wages in stand-alone firms anyways. To provide evidence that part of the link between business group affiliation and the structure of earnings is driven by ownership, we take advantage of the fact that some firms joined business groups during this sample period. We introduce firm fixed effects into our specification and exploit within-firm variation in time: we compare the earnings of same firm in two different moments of time, with different group affiliation. That is, our identification strategy exploits *changes* in business group affiliation. We also add sector-year fixed effects in order to control for other changes that might be occurring at the same time within the industry of the firm. Our results show that both average earnings and earnings dispersion increase when a stand-alone firm joins a group. The effects are persistent over time.

Using the Abowd, Kramarz, and Margolis (1999) methodology, we also control for time-varying unobserved firm-level worker composition. This method decomposes observed earnings into a worker-specific, firm-specific, and time-specific term (we follow the implementation suggested by Card, Heining, and Kline, 2013). We identify those terms because in our matched employer-employee dataset, some workers move between firms in time (which identifies worker effects) and different workers work in the same firm in the same moment of time (which identifies firm effects). We regress earnings on worker, firm, and year fixed effects. Then, we retrieve the estimated firm fixed effects, which measure average firm-level earnings controlling for unobserved worker characteristics, and also retrieve the worker's skills (i.e., worker fixed effect). After controlling for worker composition using average worker fixed effects, we find that the effect of business group affiliation on average earnings is reduced by half, while the effect on earnings dispersion remains unchanged. This suggests that group transitions are associated with changes in the average worker skills of firms, but the dispersion of worker skills remains the same.

Exploiting transitions into business groups has the advantage of allowing us to control for time-invariant firm characteristics. However, group transitions are not exogenous. Since our identification exploits the timing of the transitions, other changes might be happening at the same time that could drive both the entry into a group and its subsequent change in earnings inequality, introducing a bias in the coefficient of interest. For example, a firm might grow due to productivity boom that attracts the interest of a business group and also change earnings inequality in the firm at the same time. Although we control in the baseline specification for industry-year fixed effects there might still be selection of specific firms within industries. In order to partially address this concern, we construct a matching sample using a coarsened-exact-matching methodology (Iacus, King, and Porro, 2012). We perform exact matching on employment, average wage, standard deviation of average wage and industry. We confirm a positive effect of joining a group on average earnings and earnings dispersion, although the effect on average earnings loses statistical significance.

This paper makes contribution to several strands of the literature. First, it shows another way in which firms can influence earnings inequality: through their affiliation to an ownership network with other firms. Previous literature is focused on the impact on inequality of firm size (Song, Price, Guvenen, Bloom, and von Wachter 2018; Mueller, Ouimet, and Simintzi 2017b), the hierarchical organization of production (Caliendo, Monte, and Rossi-Hansberg, 2015); firm productivity (Autor, Dorn, Katz, Patterson, and Van Reenen, 2020), pay policies (Alvarez, Benguria, Engbom, and Moser, 2018), and imperfect competition in the labor market (Lamadon, Mogstad, and Setzler, 2019). Our paper shows that changes in the ownership structure of firms also influence earnings inequality. These results are in line with the importance of ownership structures for labor outcomes (e.g., the connection between private equity ownership and employment documented in Davis, Haltiwanger, Handley, Jarmin, Lerner, and Miranda 2014). We present evidence that common ownership increases earnings inequality due to the between and within firm components, and that the within component is driven by top workers. This suggests that paying attention to professional and managerial positions is important for understanding the effects of ownership on earnings inequality. We also find that the between component is driven partially by firms increasing the average skills of workers, while the within component is not driven by increases in the dispersion of worker skills. This implies that the increase of wages of top workers is not solely explained by the increase of skills or the human capital of top workers (Bender, Bloom, Card, Reenen, and Wolter, 2018).

Second, it shows another role for ownership networks on firm behavior. There is evidence highlighting the advantages and disadvantages of joint ownership on firm behavior. The main advantage is the creation of internal capital and labor markets that facilitate the reallocation of factors (Huneeus, Larrain, Larrain, and Prem, 2021; Giroud and Mueller, 2015, 2019). Disadvantages include that affiliated firms crowd out non-affiliated firms from financing (Almeida and Wolfenzon, 2006), and increasing firms' market power over consumers (Azar, Schmalz, and Tecu, 2018). Whether the impact on earnings inequality is an advantage or disadvantage, an intended or unintended consequence, is still up for debate.

We provide an overview of outstanding theories that could account for the impact of business groups on earnings inequality. For instance, since their impact is mostly unaffected when controlling for worker skills, it is tempting to conclude that earnings dispersion is related to rent-sharing between owners and workers (Mueller and Philippon 2011). At the same time, the hierarchies that business groups build can increase leverage on the skills of top workers, and therefore increase inequality (Garicano and Rossi-Hansberg 2006). Finally, earnings inequality may be the result of high-power incentives and tournament-like mechanisms (Lazear and Rosen 1981). Although we cannot fully disprove any of these theories, our preliminary evidence suggests that none of them has a clear advantage to explain the connection between earnings dispersion and business groups.

The remainder of the paper is structured as follows. Section 2 describes the data and presents summary statistics. Section 3 presents the evidence of the effect of business groups on earnings inequality. Section 4 exploits transitions into business groups to provide a more robust test of the effect of business groups on earnings inequality. Section 5 provides an overview of potential explanations for the impact of business groups on earnings inequality. Section 6 concludes.

2 Data

We combine two data sources to study the connection between earnings inequality and the ownership structure of firms. First, we use a matched employer-employee dataset to decompose overall earnings dispersion into between-firm dispersion of firm average earnings and within-firm dispersion in workers earnings. Second, we use a business-group dataset to link the firms in our sample according to their ownership structure. We classify firms into business group firms and stand-alone firms.

2.1 Matched Employer-Employee Dataset

For the purposes of providing unemployment insurance, 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, which keeps an administrative dataset, the Unemployment Insurance (UI) dataset. This dataset has the wage, at a monthly frequency, for each employer-employee relationship. Besides wages, firms need to report their main industry and the gender and birth date of the respective worker. The dataset does not report information of the specific professional category or occupation of each worker. Past research on worker-firm 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 private (formal) labor market in Chile. Second, since Chile's administrative datasets have unique tax IDs for both workers and firms, we can keep track of both across time and merge them to other datasets. In particular, this dataset includes listed firms, which we use to merge to the business group dataset. Finally, given that we have the employer-employee relationships, we have the entire wage distribution both within and across firms. Our main sample keeps firms that appear more than once in our dataset and that have a minimum of workers in all the years above ten.

2.2 Business Group Dataset

Chilean listed firms are required by law to report financial statements and ownership structures regularly to the local stock market regulator (Superintendencia de Valores y Seguros, SVS, during this sample period). From the universe of listed firms, we define a business group as a set of two or more listed firms with a common controlling shareholder (Buchuk, Larrain, Munoz, and Urzúa, 2014). Financial statements typically report links between corporations, but not the names of individual shareholders. 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 stakes of controlling shareholders are stable across long periods of time in the Chilean market (Donelli, Larrain, and Urzúa, 2013).

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 each group. Ownership links with private firms are reported in two ways. First, there is a list of firms that consolidate with each 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 by each listed firm. This list has information on 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%. Since 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 –public and private–

that conform each business group. During the sample period for which we have this information, 2004-2016, we identify 29 groups comprising approximately 93 listed firms and multiple private firms. Figure 1 provides an example of a business group in our data. The group has 5 listed firms: the holding company –Antarchile– at the top of the pyramid plus 4 firms in the second layer of the ownership structure.

We merge these data sets using unique tax IDs of workers and firms that are common across sources. To secure the privacy of workers and firms, we cannot observe the merged dataset and the Chilean IRS requires all results that are extracted to be calculated using at least 25 tax IDs.

2.3 Summary Statistics

Table 1 reports summary statistics four our sample covering the 13-year period 2004-2016. Our sample includes 35,410 firms, 383 of which are business-group firms (1% of total firms) and the remaining 35,027 are stand-alone firms. The sample contains 2,436,441 workers, 99,996 of which work in group firms (4% of total workers) and 2,336,445 work in stand-alone firms. The average firm in our sample employs 122 workers. Group firms are larger than stand-alone firms: they employ 3.7 times more workers than stand-alone firms (=435/118). In terms of worker characteristics, 34% of all workers are female (828,389 workers). The fraction of female workers is smaller in group firms. The average worker is 38 years old, in both group and stand-alone firms. Average tenure is 2.6 years, although it is slightly higher for group firms than for stand-alone firms. All differences between group and non-group firms are statistically significant.

3 Business Groups and Earnings Inequality

3.1 Inequality Within and Between Firms

As a first step toward understanding the contribution of business groups to earnings inequality, we investigate the variance of earnings between and within firms. Following Song, Price, Guvenen, Bloom, and von Wachter (2018), we decompose the overall cross-sectional variance of log earnings into a between-firm and within-firm component. In particular, let $y_{t,i,j}$ be the log earnings of worker i employed by firm j in period t. This can be broken down into two terms:

$$y_{i,j,t} \equiv \overline{y}_{j,t} + (y_{i,j,t} - \overline{y}_{j,t}),$$

where $y_{j,t}$ is the firm average earnings for firm j. After some algebra one can show that the overall variance can be decomposed into two terms:

$$\underbrace{\mathrm{var}(y_{i,j,t})}_{\text{Overall dispersion}} = \underbrace{\mathrm{var}(\overline{y}_{j,t})}_{\text{Between-firm dispersion}} + \underbrace{\sum \omega_j \times \mathrm{var}(y_{i,j,t}|i \in j)}_{\text{Within-firm dispersion}}. \tag{3.1}$$

That is, dispersion in overall earnings can be decomposed into the between-firm dispersion of firm average earnings and the employment-weighted sum of within-firm dispersion in worker earnings, where ω_j denotes the employment share of firm j in the sample. One could imagine two hypothetical extreme cases. First, average earnings could be identical across firms so that overall earnings inequality is completely due to variance in earnings within firms. Second, all workers could receive the same earnings within the firm so that inequality arises entirely due to differences in earnings between firms.

Figure 2 plots the three terms in equation (3.1) separately for each year between 2004 and 2016. Overall earnings inequality has remained essentially flat during our sample period. The within-firm component contributes slightly more than the between-firm component to overall inequality. Both components have basically remained unchanged during this period.

3.2 Business Groups and Between-Firm Inequality

We classify firms into two groups: business-group firms and stand-alone firms. To study how business groups contribute to overall earnings inequality through the between-firm component, we plot the average earnings of group firms and stand-alone firms. Panel A of Figure 3 shows that the average log earnings paid by group firms is 60% higher than the earnings paid by a stand-alone firms. The difference is statistically significant at the 1% level.

We regress log average firm earnings into a business group indicator variable:

$$\overline{y}_{j,t,s} = \beta \times BG_{j,t} + \gamma \times LogEmployment_{j,t} + \delta \times Controls_{j,t} + \quad {}_{t,s} + \epsilon_{j,t,s}, \tag{3.2}$$

where j, t, and s stand for firm, year, and sector respectively. $BG_{j,t}$ is a indicator variable equal to one if the firm j belongs to a business group in year t and zero otherwise. $LogEmployment_{j,t}$ is the log of the the number of workers at firm j in year t. We control for firm size with total employment because group firms are larger than stand-alone firms (Table 1), and larger firms tend to have higher average earnings than small firms. This size effect has been labeled the 'size premium' by the literature (Colonnelli, Tag, Webb, and Wolter, 2018; Bloom, Guvenen, Smith, Song, and von Wachter, 2018). $Controls_{j,t}$ is a vector of observable characteristics of firm j in year t: share of female workers, average worker age, average worker tenure, and the standard deviation of worker age.

The specification includes sector-year fixed effects ($\psi_{t,s}$) to account for unobserved time-varying industry shocks. This means that the group dummy is identified by comparing average earnings of a group firm and a stand-alone firm in the same year and sector. We cluster the standard errors of all the regressions in this paper at the firm level.

Table 2 reports the results. Column (1) confirms the existence of a 'size premium' in our sample: large firms pay higher average earnings than small firms. Column (2) adds the business group dummy on top of the size variable. If we compare a group firm with a stand-alone firm of same size, both with similar worker composition and operating in the same sector in the same year, the average earnings of the group firm is 36% higher than that of the stand-alone firm. The difference is not only quantitatively large but also highly statistically significant. This is a novel finding that we label the 'group premium': after controlling for size, group firms pay higher earnings than stand-alone firms.

In columns (3) to (12), we re-estimate equation (3.2) for different segments of the within-firm earnings distribution. For example, in column (3) we focus on the earnings bellow the 10th percentile of the distribution; in column (4) we focus on earnings between the 10th and 20th percentile, and so on. We observe a significant 'group premium' in all segments of the earnings distribution, indicating that this premium is not driven solely by top-earnings workers.

In Panel B of Table 2 we control for firm size in an non-parametric way. Instead of $LogEmployment_{j,t}$ we add dummies for each one of the one hundred percentiles of the distribution of firm size. The results are virtually unchanged, which shows that it is unlikely that some unknown polynomial function of firm size can account for the group premium.

3.3 Business Groups and Within-Firm Inequality

In Panel B of Figure 3, we plot the within-firm standard deviation of log earnings for group firms and stand-alone firms. Within-firm dispersion in group firms is 7% higher than in stand-alone firms. The difference is statistically significant at the 1% level.

We estimate a regression similar to (3.2) but using as dependent variable the standard deviation of log earnings in a firm. In this specification, we also control for firm size, because recent work has shown that firms with higher within-firm inequality tend to be larger (Mueller, Ouimet, and Simintzi, 2017b). Table 3 reports the results. Column

(1) confirms the result that within-firm inequality is higher in larger firms. Column (2) shows that the group dummy is positive and highly significant, indicating that if we compare a group firm with a stand-alone firm of the same size (and in the same sector and year), the group firm exhibits higher earnings dispersion than the stand-alone firm. The positive effect of group affiliation on earnings inequality amounts to 12% of average earnings inequality (= 0.048/0.41). Column (3) controls for 100 size buckets and the results remain unchanged.

To understand the source driving the result of higher within-firm inequality in group firms, Table 4 re-estimates (3.2) using as dependent variable the relative earnings in different segments of the distribution. Column (1) focuses on the earnings of the top 10th percentile relative to the bottom 10th percentile, column (2) compares top 10th with bottom 50th, and column (3) compares top 50th with bottom 10th. For all three cases, we observe that inequality is higher for group firms than for stand-alone firms. This means that the effects are not driven exclusively by the very top workers (those at the top 10th percentile of the earnings distribution).[2]

4 Transitions In and Out of Business Groups

4.1 Firm Fixed Effects Estimation

The results in the previous sections exploit cross-sectional variation to document a robust correlation between group affiliation and average earnings and within firm-inequality, after controlling for firm size and other firm characteristics.

However, our results could be driven by unobservable characteristics that correlate with group status and that lead to higher average earnings (or dispersion). For example, maybe business groups tend to hire high-productivity workers (which is unobservable), who would earn higher wages in stand-alone firms anyways. To provide evidence that the link between group affiliation and earnings is indeed driven by ownership, we exploit the fact that some firms in our sample changed their status from stand-alone firms to group firms and viceversa.

During the period 2004-2016, we observe 105 cases of stand-alone firms that join a group and 134 cases of group firms that leave a business group and become stand-alone. Figure 5 Panel A shows the number of transitions by year, on average there are 11 transitions per year with a maximum of 30 in 2005 and a minimum of six in 2011 and

[2]The appendix A.1 shows that the results in this section are robust to adjusting for the top-coded earnings of workers.

2013. Moreover, these transitions are scatter across different business groups: there are four groups with more than ten transitions, four groups with five to ten transitions, and 12 groups with less than five transitions. Panel B shows that transitions are scattered across sectors, although with a focus on manufacturing and telecommunications.

Table 5 presents summary statistics for firms transitioning to a group the year before the transition. These firms tend to be smaller in terms of employment, they pay lower average wages, they have younger workers and with lower tenure than the average firm in a group (see Table 1).

We introduce firm fixed effects into our specification in (3.2) and exploit within-firm variation in time: we compare the earnings of same firm before and after group a transition. The identification from this strategy comes from the timing of the event. Naturally, other things might be changing at the same time, which could bias the strategy. For example, a certain industry might be booming, and a business group might want to acquire a firm from that industry. If the industry is booming because of productivity growth, it might be that this growth explains both the entry into the business group and the consequent change in distribution of earnings. Sector-year fixed effects can partially address this concern. Thus, identification comes from variation across the same firm over time, relative to the average within-firm variation in the same industry and year.[3]

Table 6 reports the results. Column (1) focuses on average earnings and column (2) on within-firm inequality. Column (1) shows that average earnings increases by 3.7% when a stand-alone firm joins a group (likewise, average earnings decrease by 3.7% when a firm leaves a group). Column (2) we find that being part of a group increase the dispersion of earnings by 0.016, which represents a 3.9% increase with respect to the mean (=0.016/0.412). Column 3 shows that there is no impact on total employment when firms enter a business group.

In Table 7 we conduct the same analysis for the log average wage in each decile of the wage distribution. We find that there is a strong increase in the average wage of workers at the top half of the wage distribution, but little or no change for workers at the bottom half. The effect of group affiliation is almost monotonically increasing from bottom workers to top workers.

[3] One potential concern with this two-way fixed effect approach is that the estimated coefficient can differ from the true ATT because of negative weights in individual ATT due to a comparison between late treated with early treated and treatment heterogeneity (De Chaisemartin and d'Haultfoeuille, 2020; Borusyak and Jaravel, 2017). We follow De Chaisemartin and d'Haultfoeuille, 2020 by estimating the relevance of the negative weights. We find that they account for 0.3% of the estimated coefficient, suggesting that this is a very minor issue in our setting.

4.2 Controlling for Unobserved Worker Composition

As an alternative strategy to control for unobserved worker composition, we use the Abowd, Kramarz, and Margolis (1999) method, henceforth AKM, to decompose observed earnings into a worker-specific, firm-specific, and time-specific term. We follow the implementation suggested by Card, Heining, and Kline (2013). We identify those terms by exploiting the fact that in our data some workers move between firms in time (which identifies worker effects) and different workers work in the same firm in the same moment of time (which identifies firm effects). In particular, we estimate the following model:

$$y_{i,j,t} = \theta_i + \phi_j + X'_{i,t}\Omega + \tau_t + \epsilon_{i,j,t}, \tag{4.1}$$

where i, j, and t stand for worker, firm, and year respectively. $y_{i,j,t}$ is the log earnings of worker i, in firm j, at year t. In this model θ_i captures the earnings related to fixed characteristics of the worker (e.g., ability or returns to education), ϕ_j captures the differences in earnings related to fixed characteristics of the firms (e.g., bargaining power or compensating differentials). We also include year fixed effects, τ_t, that capture aggregate shocks that might affect earnings, and a third degree age polynomial ($X_{i,t}$) as in Song, Price, Guvenen, Bloom, and von Wachter (2018). The error term, $\epsilon_{i,j,t}$, measures transitory earnings fluctuations.

As shown by AKM, the separate identification of worker and firm fixed effects can be done only within a set of firms and workers who are connected through worker mobility. This is known as the largest connected set. For the Chilean economy between 2004 and 2016, the largest connected set comprises 99.9% of all the firm-worker-year observations. Thus, in our case the restriction coming from the largest connected set is not binding. In Table A.2 we shows summary statistics of the workers that switch firms. We document that labor mobility is high: around 64% of the workers had more than one job during our sample of analysis.[4]

We retrieve the firm and worker fixed effects from equation (4.1), and use them in between-firm and within-firm strategies described in the previous sections. First, we focus in the between-firm strategy. The estimated firm fixed effects from AKM capture the time-invariant average earnings that are unrelated to the worker composition of firms. In Panel A of Figure 4, we plot these estimated firm fixed effects by group affiliation.

[4]The main assumption behind the identification of the parameters of interest is that the error satisfies the strict exogeneity assumption, i.e. $E[\epsilon_{i,j,t}|\theta_i, \phi_j, \tau_t, X_{i,t}] = 0$. In the context of the AKM model, this is known as *exogenous mobility*: mobility is not related with the unobserved error component. We asses the validity this assumption in several ways following Card, Heining, and Kline (2013), see Appendix A.2.

We find that there is a significant positive relationship between group affiliation and average earnings of firms (p-value of 0.00). This difference is by construction unrelated to unobserved worker effects. Given that the firm fixed effects are standardized, the results imply that group firms pay average earnings that are 1.08 standard deviations larger than stand-alone firms.

Next, we apply AKM to our within-firm identification strategy. We estimate firm fixed effects from equation (4.1), but we consider a firm that changed group status as two different firms: if firm A joined a business group, we consider firm A as two different firms, before and after its transition. This means that for firms that switch their group status, we estimate two different set of fixed effects, before and after their transition. Panel B of Figure 4 plots firm fixed effects before and after entering a group. The case of firms exiting a group is reported in Panel C. We find that joining a group increases average earnings in 0.09 standard deviations (p-value of 0.03), while exiting a group decreases average earnings by 0.08 standard deviations (p-value of 0.05). This is our preferred empirical strategy used in the paper. By combining the within-firm strategy with the AKM adjustment, we can control not only for unobserved worker composition, but also for unobserved worker composition that changes in time.

As an additional test, we re-estimate (3.2) controlling for the estimated AKM worker fixed effects. In particular, we add the average and standard deviation of the worker fixed effect of firm j in year t.[5] Before discussing the results we must acknowledge that by adding the time-variant composition of workers we are probably adding a "bad control" (Angrist and Pischke, 2008) given that entering or exiting a business group likely changes worker composition. Therefore, our results must be interpreted with caution.

As seen in Table 8, the effect of group affiliation on average earnings remains positive and significant (1.4%), but the size of the effect is reduced by more than half, compared to the specification that did not control for worker composition (Column 1 of Table 6). This suggests that entering (exiting) a business group increases (decreases) the average skills of workers. On the other hand, the effect on within-firm earnings dispersion for the firms that changed affiliation remains unchanged. This suggests that, although average skills might have changed, the dispersion of skills did not change.

Finally, consider the augmented AKM model where we include business-group effects

[5]It has been shown that second moments of the estimated fixed effects can be biases (see Abowd, Kramarz, Lengermann, and Pérez-Duarte, 2004). Because in our case we are only controlling by it and we are not particularly interested in the point estimate this problem should be of second order.

(γ_g):

$$y^r_{i,j,t} = \theta_i + \phi_j + \gamma_g + \xi_{i,j,t}, \tag{4.2}$$

where $y^r_{i,j,t}$ is the residual of worker earnings once the age polynomial and year effects from (4.1) have been removed. We can identify the group effects separately from firm effects because some firms move in and out of groups. The variance decomposition of worker earnings can then be written as:

$$\begin{aligned} var(y^r_{i,j,t}) = {} & var(\theta_i) + var(\phi_j) + var(\gamma_g) + var(\xi_{i,j,t}) + 2cov(\theta_i, \phi_j) \\ & + 2cov(\theta_i, \gamma_g) + 2cov(\phi_j, \gamma_g). \end{aligned} \tag{4.3}$$

Besides the variance of each element, the covariances are interesting to capture sorting effects. For example, a positive $cov(\theta_i, \phi_j)$ implies that strong workers are matched with strong firms. Similarly, a positive $cov(\phi_j, \gamma_g)$ implies that strong firms are affiliated to strong business groups.

It can be illustrative to further decompose the variance as follows:

$$\begin{aligned} var(y^r_{i,j,t}) = {} & var(\theta_i - \bar{\theta}_{j,t}) + var(\xi_{i,j,t}) + var(\bar{\theta}_{j,t}) + var(\phi_j - \bar{\phi}_{g,t}) + var(\bar{\phi}_{g,t}) \\ & + var(\gamma_g) + 2cov(\theta_i, \phi_j) + 2cov(\theta_i, \gamma_g) + 2cov(\phi_j, \gamma_g), \end{aligned} \tag{4.4}$$

where $\bar{\theta}_{j,t}$ represents the average worker effect in firm j in year t, and $\bar{\phi}_{g,t}$ represents the average firm effect in group g in year t. The first two elements on the right hand side of equation (4.4) represent the within-firm sources of earnings inequality. The rest of the terms capture between-firm inequality.

The results from the different AKM models are presented in Table 9. The baseline decomposition does not include group effects. As seen in column 1, worker effects account for 51% of the earnings variance. The variance of firm effects and the positive covariance between worker and firm effects account for 18% and 19% respectively. In column 2 we further split the variance of worker effects into the variance of average worker effects ($var(\bar{\theta}_{j,t})$) and the variance of the demeaned worker effects ($var(\theta_i - \bar{\theta}_{j,t})$). This last within-firm component accounts for two thirds of total worker effects. In columns 3 and 4 we add the group effects to the decomposition. They have a negligible effect on the overall variance decomposition of earnings, which is perhaps not too surprising given that group firms represent close to 1% of the firms in the economy (see Table 1).

4.3 Controlling for Selection Bias with Matching

In the previous section, we used the transitions of firms in and out of business groups to control for time-invariant unobserved characteristics. Thus, the identification was given by within-firm variation of firms joining and exiting business groups relative to within-firm variation for the average firm (in the same industry and year). This would be a sufficient strategy to identify the effect of business groups on earnings inequality if the affiliation of firms to business groups were random. However, if this affiliation is not random, then the previous results are potentially biased due to selection of firms into business groups. Other changes might be occurring at the same time of the transition, and those changes might be driving both the affiliation to a business group together with its effects on labor outcomes. For example, a firm might be growing due to an increase in productivity, and in turn such increase in productivity can draw the attention of a business group to acquire it. Firms that grow in size tend to increase their earnings inequality as well.

To address the selection bias of business group affiliation, we implement a Coarsened Exact Matching following Iacus, King, and Porro (2012). This methodology looks for control firms that are observationally equivalent to the treated firms up to the moment of their affiliation to a group, so that all residual variation at that moment is random. This matching is implemented in two rounds, with tighter bounds in the first round. In both rounds we match each group firm with potential control firms according to several firm characteristics: sector, number of workers, total payroll, and the standard deviation of log wages. In the first round we use deciles of the empirical distribution to create the stratas. For example, if a firm that becomes affiliated to a group is in the top decile according to the number of employees, then the control firms are also in that top size decile. A strata is defined by the combination of the deciles of the different sorting variables where the group firm is located before affiliation. In the second round we use quartiles of the empirical distribution to find matches. Overall, we match 104 out of the 105 transitions into business groups, 81 in the first round and 23 in the second round. We keep all the potential controls for each group firm, although our results are weighted by the number of control firms available in each match.

The main regression takes the form of a matching difference-in-differences:

$$y_{j,r,t} = \beta \times Entry_j \times Post_{j,t} + \alpha_j + \alpha_{r,t} + \epsilon_{j,r,t}, \tag{4.5}$$

where j, t, and r stand for firm, year, and strata, respectively. $Entry_j$ is a dummy that takes the value one if the firm j entered a business group, while $Post_{j,t}$ is a dummy that takes the value one after a firm enters a group or for the control of that firm in the same years. α_j and $\alpha_{r,t}$ are firm fixed effects and strata-year fixed effects. Therefore we are controlling for fixed characteristics at the firm level, as well as comparing the treated firm with its control firms within a given year. In this way β, our parameter or interest, measures the difference in outcome $y_{j,r,t}$ between firms that enter and stand-alone firms, before and after the transition, controlling for fixed firm characteristics.

Table 10 shows the main results for the wage premium and wage inequality. We present results using all controls (columns 1 and 3) and the best available control based on the propensity score of the matching (columns 2 and 4). We find that after affiliation to a business group, firms increase the average wage by 2.2% (column 1). However this effect is not statistically significant. The effect on wage inequality is stronger and robust. After affiliating to a group, firms experience an increase in wage inequality between 0.019 and 0.024 (columns 3 and 4), which is in line with our previous estimates. In Figure 6 it can be seen that there are no parallel trends before affiliation for both our outcomes, thus supporting the use of our matching difference-in-differences as a plausible identification strategy. In the case of the standard deviation of earnings, the increase in inequality can be seen once the firm enters the group.[6]

Table 11 presents the results on log wages for different segments of the wage distribution. The effect is larger, and statistically significant at the 10% level, among workers in the top decile (column 11). Panel B shows that there are no relevant effects on the wages of incumbents, i.e., workers who are employed at the firm before the transition. Panel C shows that there is employment growth at the firm after entering a group, particularly so for top workers. Hence, new top workers are entering the firm after it becomes affiliated to a business group.

Studying the wages of new workers is slightly more complicated since it is hard to define a pre-treatment wage for them. By definition, these new workers do not work at the firm before the affiliation to the business group. To at least partially address this issue, we study the relative wage of entrants and incumbents in the post period. We show the results in Table 12. We find that the wages of new workers relative to incumbent workers are close to 11% higher in group firms (column 1). The effect can be seen in

[6]This figure presents a dynamic version of equation (4.5):

$$y_{j,r,t} = \sum_{j=-3}^{J=3} \delta_k \times Entry_j \times I[j = k] + \alpha_j + \alpha_{r,t} + \epsilon_{j,r,t}, \tag{4.6}$$

where k is the relative year to the transition year. We omit the dummy for $k = -1$ in this way δ_k can be interpreted as the differential change in the outcome for firms that transition to a business group relative to their controls in year k relative to year -1. By looking at the coefficients in the years prior to the transition we can at least partially assess the validity of the parallel trends assumption.

bottom workers (column 2), but it is stronger in top workers (column 11). One piece of suggestive evidence regarding the characteristics of the new entrants is that some of them come from other firms in the same business group. In fact, among top workers, we find the largest share of new workers coming from the same business group (see Figure 7).

5 Potential Explanations

In this section we ideas for understanding the effects of ownership networks, such as business groups, on average wages and the dispersion of wages within firms. We present preliminary tests based on the heterogeneity of our results across business groups of different characteristics. In particular, in Table 13 we add interactions of the business group indicator with group characteristics (Z) to equation (3.2). The dimensions of heterogeneity that we employ are only coarse proxies associated with different mechanisms, but they do not exhaust all possibilities. Therefore, this section is only exploratory in nature. At the same time, we do not find clear evidence in favor of any particular theory, which invites more future research in this area.

5.1 Rent Sharing

The fact that dispersion survives when we control for worker effects (see Table 8) suggests that some of the wage differences can be due to rent-sharing between owners and workers. For instance, there is recent evidence on rent-sharing in Kline, Petkova, Williams, and Zidar (2019). Some of this may simply be rent extraction due to agency problems with top management (Bebchuk, Fried, and Walker 2002). However, the presence of strong controlling shareholders in all these ownership structures sheds doubts on that interpretation. Alternatively, rent-sharing may be a sign of nepotism (Pérez-González 2006). However, the impact on entire cohorts of workers suggests that pure nepotism is unlikely to explain the results. Perhaps some family members and friends are among those employees that enter firms as they become affiliated to a group, but it is hard to believe that the effect can drive firm-wide effects.

A hypothesis with more potential empirical traction has to do with the role of family firms in labor relations. Mueller and Philippon (2011) argue that family ownership may be particularly suited to handle labor relations, and part of that can be reflected in rent-sharing. We call this the paternalistic hypothesis. In order to implement this idea we split our sample of business groups into those with a family as controlling shareholder and those with other controlling shareholders (e.g., foreign multinationals, blocks of large shareholders, the state, etc.). We see in columns 1 and 4 of Table 13 that the interaction of the group dummy with family ownership is negatively related to average earnings and the standard deviation of earnings. The effect is not statistically significant. Hence, contrary to the paternalistic hypothesis, there is no evidence of more rent-sharing among family business groups compared to other groups.

5.2 Skill Differentials

The AKM methodology suggests that skill differentials cannot account for the effects of business groups. However, some skills may not be captured by the AKM decomposition, in particular those skills that are not innate to the worker, but instead acquired at the firm. This includes intangible skills, such as management practices or those related to the organizational culture of the firm (see, for instance, Atalay, Hortaçsu, and Syverson 2014, and Huneeus, Larrain, Larrain, and Prem 2021). Another possibility is that business groups can increase leverage on the innate skills of workers by forming a hierarchy that spans across firms. In this respect, the literature shows that hierarchies are a way to increase the returns on the knowledge of top workers (see Garicano and Rossi-Hansberg 2006). Hence, although there may be no difference in the innate skills of workers in group and non-group firms, the productivity of workers can be higher in a business group hierarchy. In turn, productivity differentials are likely to be reflected in the wages paid in group and non-group firms.

Although it is hard to bring this hypothesis to the data, we conjecture that business groups with more firms and/or more total employees are likely to either provide more intangible skills to their employees, or to have more complex hierarchies. The continuous interaction with other group firms can require more management skills and a stronger organization culture. Similarly, if there are more employees there is more space to leverage on the skills of a few top workers.

In columns 2-3 and 5-6 of Table 13 we include interactions of the group dummy with both of these characteristics: the number of firms and the number of employees in the group. Although we find positive interactions in the regressions with average worker earnings, the effects are small and not statistically significant. When it comes to the standard deviation of earnings, the coefficient on the interaction is negative and even statistically significant in the case of total number of employees. Hence, groups with more employees seem to have smaller within-firm inequality, contrary to the skills hypothesis.

5.3 Incentives

Incentives represent a final family of theories that could address our results. High-power incentives, such as those given by equity-linked compensation, are likely to apply to only a few top positions within the firm such as the CEO (Murphy 1999). Hence, it is unlikely that they can explain a widespread effect on wages as we document. For example, even the top decile of workers in the average group firm contains more than 40 employees.

Another incentive-related hypothesis argues that business groups can give implicit unemployment insurance by transferring employees towards other group firms when one firm fails (Cestone, Fumagalli, Kramarz, and Pica 2017). The cost of such insurance for employees would be lower wages in group firms. We find the opposite in our sample, which suggests that the insurance motive is not the best explanation for our results.

Within-firm inequality may not only be a side-product of incentives for top employees, but perhaps an integral part of the compensation policy. For instance, the tournament literature suggests that the prize of the tournament (e.g., wages in top positions), and hence the dispersion of earnings within the firm, have to increase when there are more tournament participants (Lazear and Rosen 1981). This is necessary to keep workers incentivized as the probability of winning the tournament goes down. An implication of this tournament-like design is that within-firm inequality should be higher in those business groups with more employees. As already seen in column 6 of Table 13, this is hardly the case in our sample. Overall, there is little evidence that incentives can account for our results.

6 Conclusions

We use a matched employer-employee dataset and data on the ownership network of business groups from Chile to document a novel relationship between the ownership network of firms and earnings inequality. Exploiting transitions of firms into and out of business groups, we show that groups contribute to higher earnings inequality along two dimensions. First, group firms pay higher average wages than, otherwise similar, stand-alone firms, increasing between-firm inequality. We label this difference the “group premium”. Second, the dispersion of wages inside group firms is higher than inside stand-alone firms, increasing within-firm inequality.

In terms of mechanisms, we show that that the effects of group affiliation on the between- and within-firm components of inequality are explained primarily by the earnings of workers at the top of the within-firm wage distribution. That is, when a firm enters a business group, the earnings of top workers increase, which leads to both higher average earnings and more earnings dispersion. We also show that the increase of wages of top workers is driven by the new workers that enter the group, who are paid more than incumbent workers.

Our findings shed light on how the growth of business groups can affect the distribution of income in the economy. Our evidence suggests that the owners of capital share some of the benefits of business group growth with workers, particularly top workers. Explaining these facts, potentially through differences in worker skills, incentives, or rent-sharing practices in business groups is an interesting avenue of future research.

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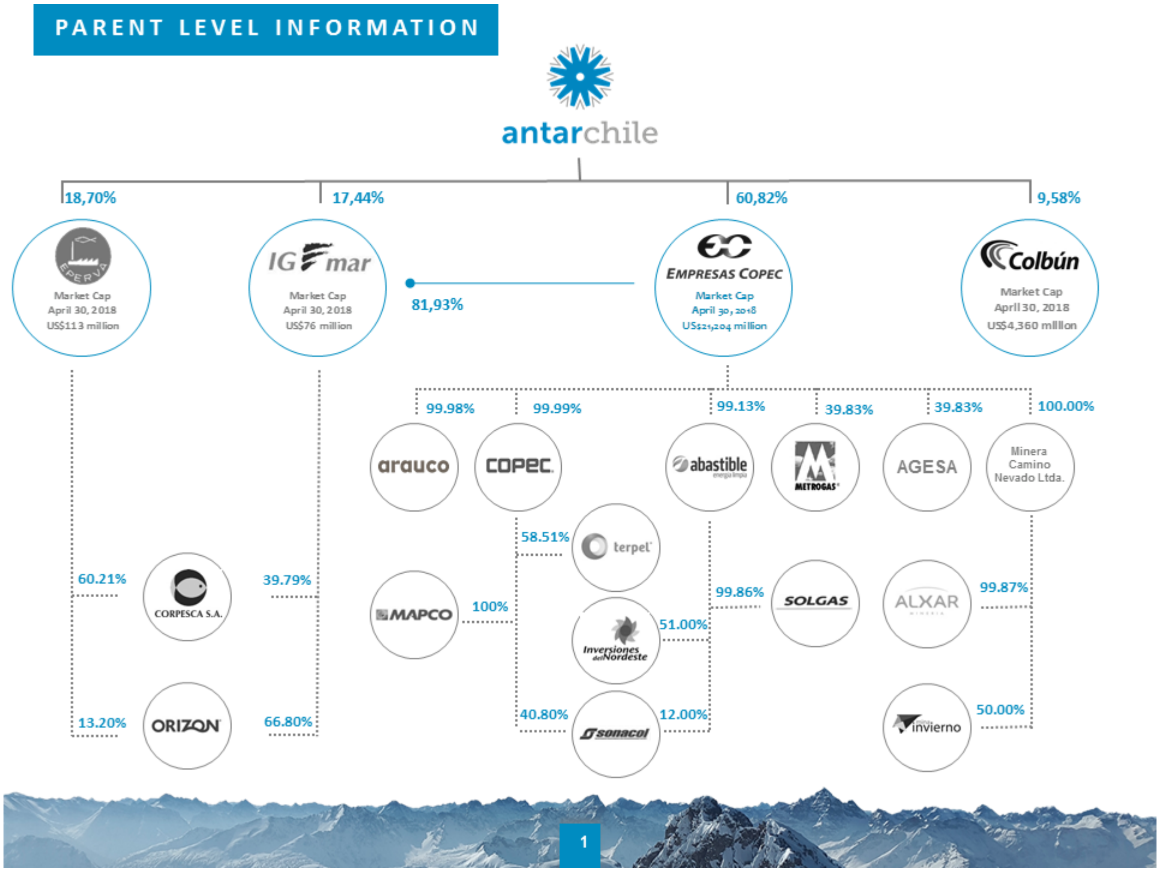
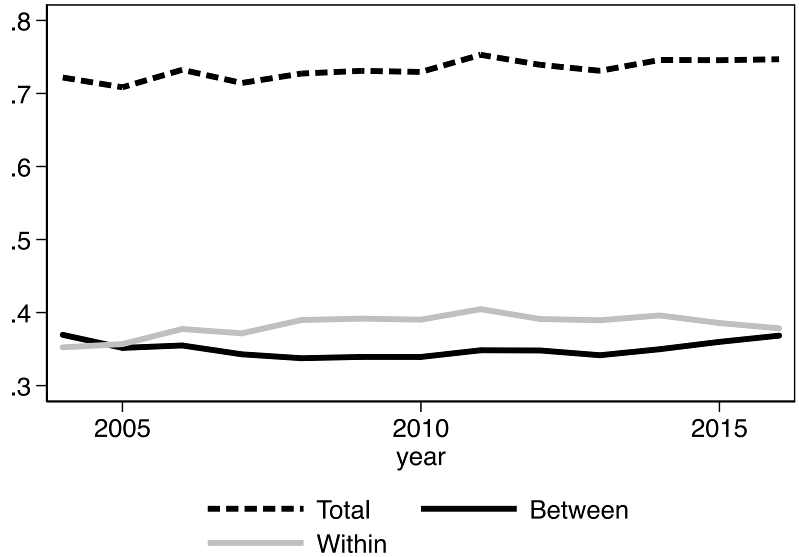
Figure 1: Example of Business Group Ownership Structure: Antarchile



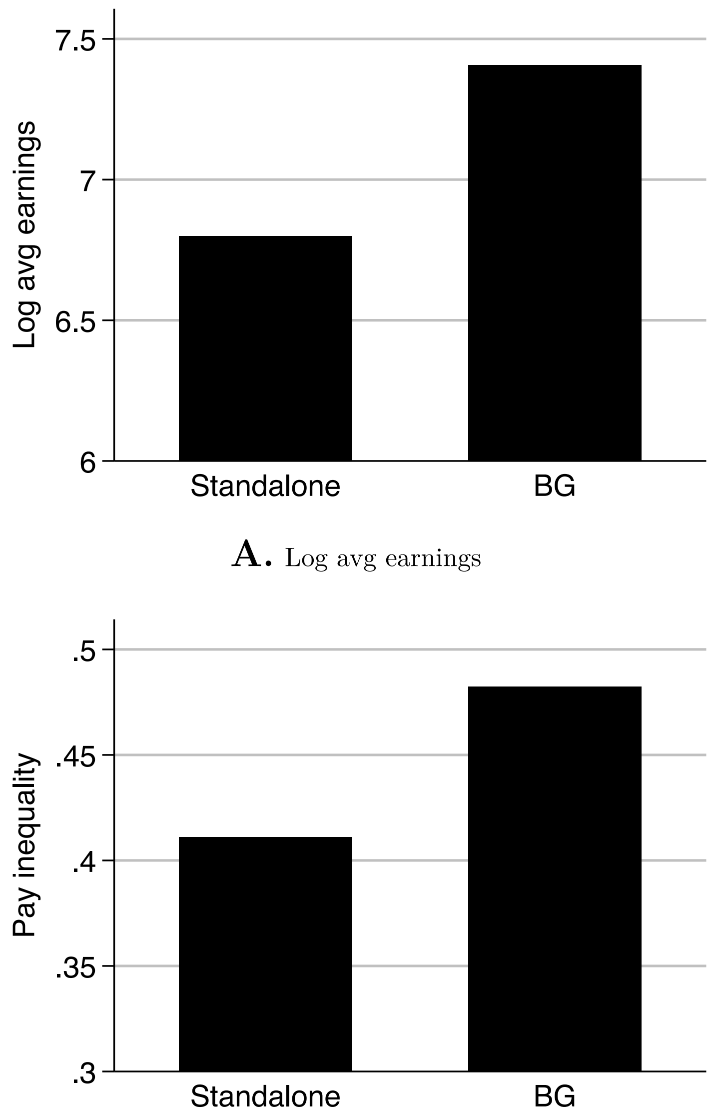
Notes: This figure presents the ownership structure of Antarchile, one of the largest business groups in Chile.

Figure 2: Evolution of earnings dispersion



Notes: This figure shows the evolution of the overall dispersion decomposing it by between and within-firm dispersion as presented in equation (3.1).

Figure 3: BG affiliation, earnings, and within-firm dispersion

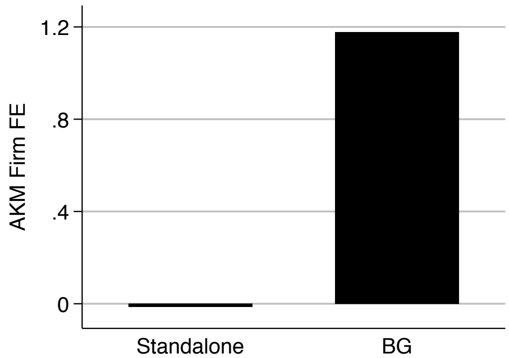


A. Log avg earnings

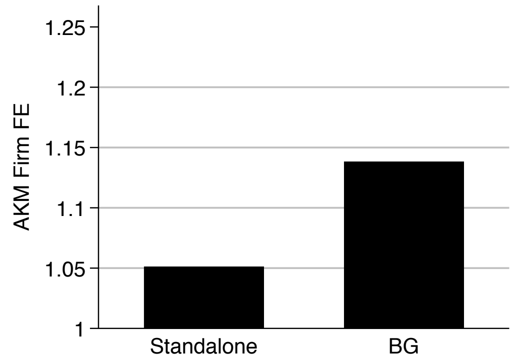
B. Earnings dispersion

Notes: This figure shows the average of log average earnings and SD of log wages by business group affiliation. In panel A the p-value of the difference is 0.00, while in panel B is 0.00.

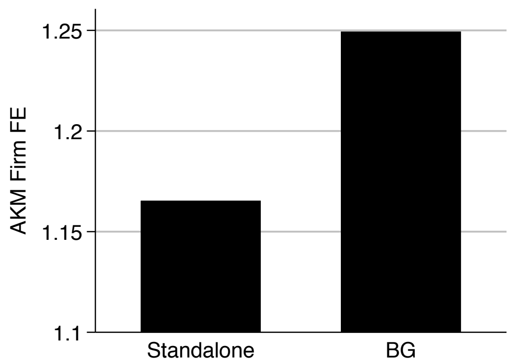
Figure 4: Business group affiliation, earnings, and within-firm dispersion



A. Business group affiliation



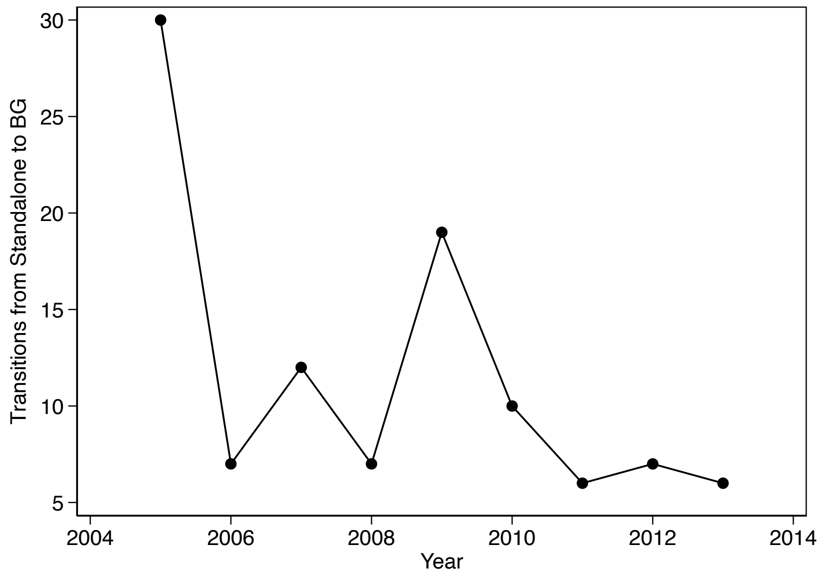
B. Entering a business group



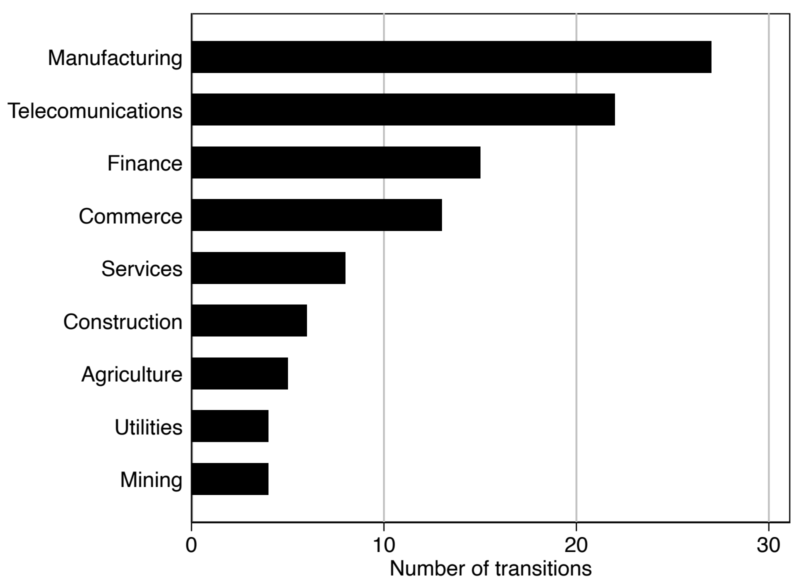
C. Exiting a business group

Notes: This figure shows the average of AKM fixed effects as estimated in equation (4.1) by business group affiliation. To ease interpretation the fixed effects are standardize by the mean and standard deviation. In this way the y-axis can be interpreted in terms of standard deviations of the fixed effect. In panel A the p-value of the difference is 0.00, while in panels B and C it is 0.03 and 0.05 respectively.

Figure 5: Transitions into Business Groups



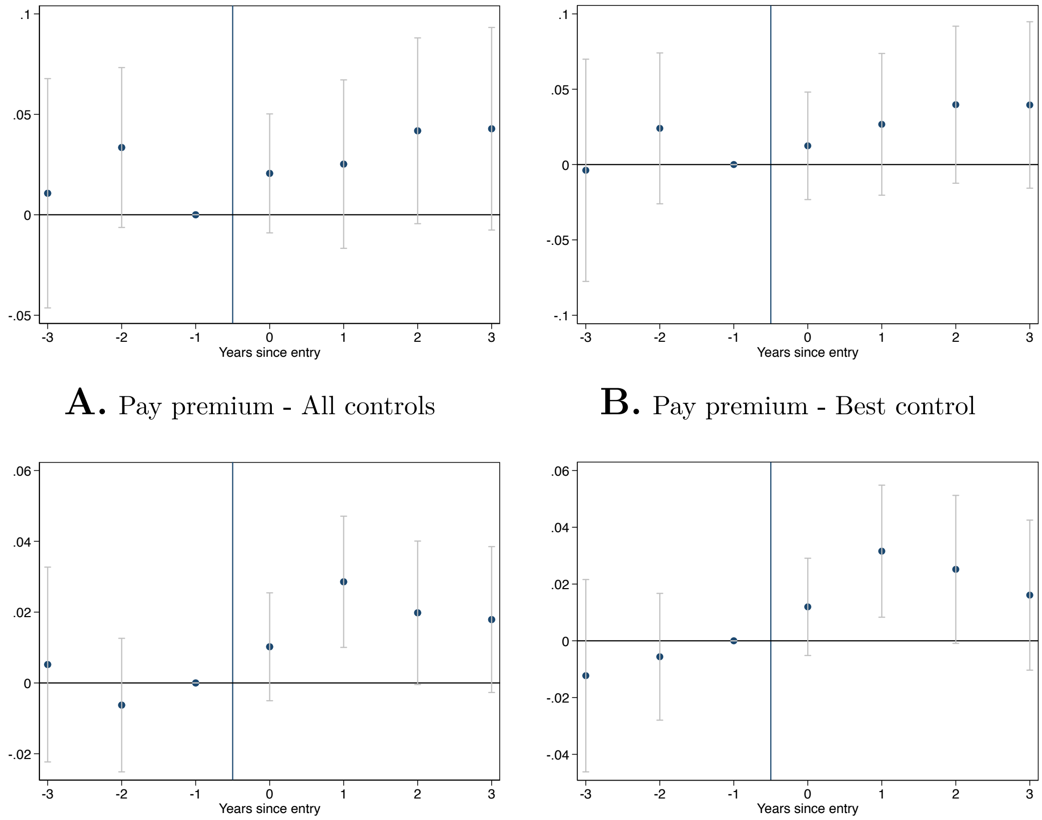
A. Evolution of transitions



B. Distribution by sector

Notes: This figure shows the number of transitions of stand-alone firms that join business groups in our sample (Panel A) and the distribution of transitions into business groups by sector (Panel B).

Figure 6: Dynamic Effects of Entering a Business Group



A. Pay premium - All controls

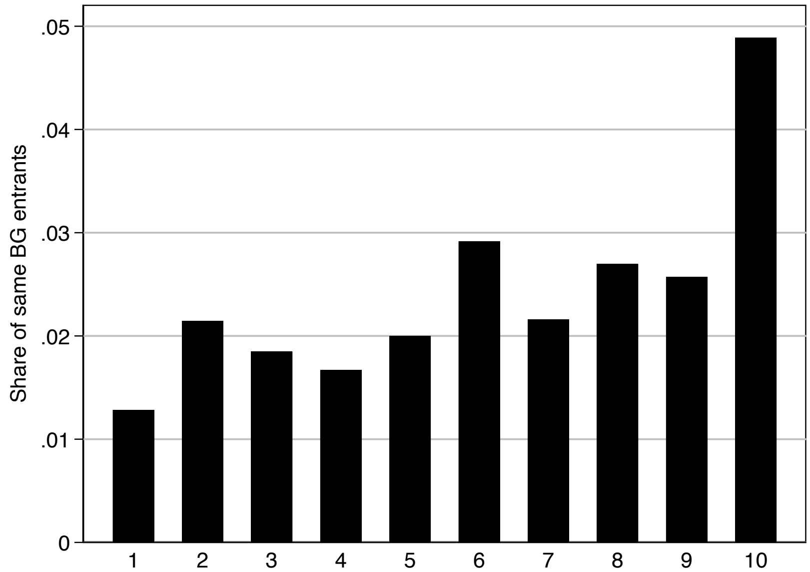
B. Pay premium - Best control

C. SD earnings - All controls

D. SD earnings - Best control

Notes: This figure present the coefficients from specification (4.6). Confidence intervals at 95% are presented in grey lines.

Figure 7: Share of Same Business Group Entrants by Wage Decile



Notes: This figure presents the share of entrants from the same business group from the year of transition up to three years after by decile of the wage distribution before the transition.

Table 1: Summary statistics

	(1) All firms	(2) Business-group	(3) Stand-alone	(4) Difference p-value
Number of firms	35,410	383	35,027	
Total workers	2,436,441	99,996	2,336,445	
Firm employment	122.76	435.45	118.97	316.48
	(401.38)	(942.87)	(388.88)	[0.00]
Log Average earnings at the firm	6.81	7.41	6.80	0.60
	(0.52)	(0.48)	(0.52)	[0.00]
Log 25th percentile of earnings at the firm	6.37	6.87	6.36	0.51
	(0.43)	(0.51)	(0.42)	[0.00]
Log 50th percentile of earnings at the firm	6.61	7.17	6.60	0.57
	(0.50)	(0.56)	(0.49)	[0.00]
Log 75th percentile of earnings at the firm	6.85	7.49	6.84	0.57
	(0.58)	(0.57)	(0.57)	[0.00]
Firm std dev of earnings	0.41	0.48	0.41	0.07
	(0.16)	(0.11)	(0.16)	[0.00]
Workers tenure	2.60	2.92	2.60	0.32
	(2.22)	(2.37)	(2.21)	[0.00]
Workers age	37.90	37.30	37.91	-0.61
	(4.71)	(3.68)	(4.72)	[0.00]
Female workers	0.34	0.24	0.34	-0.10
	(0.28)	(0.18)	(0.28)	[0.00]

Notes: This table presents summary statistics for all the firms, and then for business-group and stand-alone firms. Standard deviations are presented in parenthesis.

Table 2: Business Group Affiliation and Average Earnings

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	All		0-10	10-20	20-30	30-40	40-50	50-60	60-70	70-80	80-90	90-100
Panel A												
Business Group		0.363***	0.246***	0.275***	0.296***	0.316***	0.336***	0.357***	0.377***	0.403***	0.428***	0.427***
		(0.022)	(0.021)	(0.022)	(0.023)	(0.024)	(0.025)	(0.026)	(0.026)	(0.027)	(0.026)	(0.024)
Log employment	0.087***	0.082***	0.038***	0.058***	0.064***	0.070***	0.073***	0.078***	0.087***	0.096***	0.112***	0.132***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
R-squared	0.300	0.305	0.295	0.325	0.323	0.320	0.319	0.319	0.317	0.308	0.292	0.266
Panel B												
Business Group		0.374***	0.251***	0.282***	0.304***	0.326***	0.346***	0.368***	0.389***	0.416***	0.444***	0.444***
		(0.021)	(0.021)	(0.022)	(0.023)	(0.024)	(0.025)	(0.025)	(0.026)	(0.026)	(0.025)	(0.023)
R-squared		0.310	0.300	0.329	0.328	0.324	0.323	0.324	0.322	0.313	0.298	0.274
Observations	258,322	258,322	258,322	258,322	258,322	258,322	258,322	258,322	258,322	258,322	258,322	258,322
Sector-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Employment centiles FE (Panel B)		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is the logarithm of the average earnings in the firm (column 1) and the logarithm of the average earnings in decile $[j, j+10]$ for $j = [0, 10, 20, 30, 40, 50, 60, 70, 80, 90]$. *Business Group* is a dummy that takes the value one if a firm is part of a business group. *Log employment* is the logarithm of the total employment of the firm. The set of baseline controls include average tenure of workers, the share of female workers, and the workers' average age and standard deviation. Robust standard errors are clustered at the firm level.

Table 3: Business Group Affiliation and Within-firm Inequality

	(1)	(2)	(3)
	Standard Deviation of Log Earnings		
Business Group		0.048***	0.051***
		(0.006)	(0.006)
Log employment	0.022***	0.021***	
	(0.001)	(0.001)	
Observations	258,322	258,322	258,322
R-squared	0.138	0.139	0.143
Sector-Year FE	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes
Employment centiles FE	No	No	Yes
Mean DV	0.412	0.412	0.412
SD DV	0.160	0.160	0.160

Notes: The dependent variable is the standard deviation of the logarithm of earnings. *Business Group* is a dummy that takes the value one if a firm is part of a business group. *Log employment* is the logarithm of the total employment of the firm. The set of baseline controls include average tenure of workers, the share of female workers, and the workers' average age and standard deviation. Column 3 adds dummies for each centile of the empirical distribution of employment. Robust standard errors are clustered at the firm level.

Table 4: Business Group Affiliation and Within-firm Inequality

	(1)	(2)	(3)
	Inter-decile range		
	90-10	90-50	50-10
Business Group	0.559***	0.164***	0.183***
	(0.065)	(0.026)	(0.025)
Log employment	0.168***	0.057***	0.044***
	(0.007)	(0.003)	(0.002)
Observations	258,322	258,322	258,322
R-squared	0.159	0.079	0.175
Sector-Year FE	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes
Mean DV	2.925	1.660	1.729
SD DV	1.492	0.552	0.598

Notes: The dependent variable is the ratio of the average wages in the decil j over the average ones in decile j', where $j = 10, 50, 90$. *Business Group* is a dummy that takes the value one if a firm is part of a business group. *Log employment* is the logarithm of the total employment of the firm. The set of baseline controls include average tenure of workers, the share of female workers, and the workers' average age and standard deviation. All regressions include sector-year fixed effects. Robust standard errors are clustered at the firm level.

Table 5: Summary Statistics for Firms Transitioning to Business Group

	(1) Mean	(2) Standard deviation
Firm employment	364.52	955.86
Log Average earnings at the firm	7.24	0.50
Log 25th percentile of earnings at the firm	6.75	0.49
Log 50th percentile of earnings at the firm	7.07	0.53
Log 75th percentile of earnings at the firm	7.72	0.50
Firm std dev of earnings	0.49	0.12
workers tenure	1.96	1.43
Workers age	35.99	8.83
Female workers	0.25	0.20

Notes: This table presents summary statistics for firms transitioning to business groups in the year before the transition.

Table 6: Business Group Transitions

	(1) Log average earnings	(2) Earnings std dev	(3) Log employment
Business Group	0.037**	0.016***	-0.030
	(0.015)	(0.006)	(0.043)
Log employment	-0.034***	-0.011***	
	(0.002)	(0.001)	
Observations	258,017	258,017	258,015
R-squared	0.950	0.830	0.888
Sector-Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes
Mean DV	6.806	0.412	1.169
SD DV	0.520	0.160	0.990

Notes: The dependent variable is the logarithm of the average earnings in the firm (columns 1), the standard deviation of the logarithm of earnings (columns 2), and the logarithm of employment (column 3). *Business Group* is a dummy that takes the value one if a firm is part of a business group. The set of baseline controls include average tenure of workers, the share of female workers, and the workers' average age and standard deviation. All regressions include firm fixed effects and sector-year fixed effects. Robust standard errors are clustered at the firm level.

Table 7: Business Group Transitions and Earnings by Decile

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	0-10	10-20	20-30	30-40	40-50	50-60	60-70	70-80	80-90	90-100
Business Group	-0.002	0.014	0.022	0.032*	0.034*	0.042**	0.038*	0.039**	0.045**	0.053***
	(0.018)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.020)	(0.019)	(0.015)
Log employment	-0.025***	-0.007***	-0.008***	-0.009***	-0.013***	-0.016***	-0.017***	-0.020***	-0.020***	-0.017***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Observations	258,017	258,017	258,017	258,017	258,017	258,017	258,017	258,017	258,017	258,017
R-squared	0.857	0.905	0.920	0.927	0.932	0.938	0.941	0.942	0.938	0.922
Sector-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is the logarithm of the average earnings in decile $[j, j+10]$ for $j = [0, 10, 20, 30, 40, 50, 60, 70, 80, 90]$. *Business Group* is a dummy that takes the value one if a firm is part of a business group. The set of baseline controls include the logarithm of the total employment of the firm, average tenure of workers, the share of female workers, and the workers' average age and standard deviation. Robust standard errors are clustered at the firm level.

Table 8: Controlling for AKM Workforce Characteristics

	(1) Log average earnings	(2) Earnings std dev	(3) Log employment
Business Group	0.014**	0.015**	-0.030
	(0.007)	(0.006)	(0.043)
Log employment	0.029***	0.002***	
	(0.001)	(0.001)	
Observations	258,015	258,015	258,015
R-squared	0.974	0.857	0.888
Sector-Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes
AKM Controls	Yes	Yes	Yes
Mean DV	6.806	0.412	1.169
SD DV	0.520	0.160	0.990

Notes: The dependent variable is the logarithm of the average earnings in the firm (columns 1), the standard deviation of the logarithm of earnings (columns 2), and the logarithm of employment (column 3). *Business Group* is a dummy that takes the value one if a firm is part of a business group. The set of baseline controls include average tenure of workers, the share of female workers, and the workers' average age and standard deviation. The *AKM controls* includes the average and the standard deviation of worker fixed effect, estimated from equation (4.1). All regressions include firm fixed effects and sector-year fixed effects. Robust standard errors are clustered at the firm level.

Table 9: Earnings variance decomposition

	(1)	(2)	(3)	(4)
	Baseline		Adds group effects	
Variance of worker effects	0.21 (0.51)		0.21 (0.51)	
Variance of avg worker effects		0.07 (0.17)		0.07 (0.17)
Variance of demean worker effects		0.14 (0.34)		0.14 (0.34)
Variance of firm effects	0.07 (0.18)	0.07 (0.18)	0.07 (0.18)	
Variance of avg firm effects				0.00 (0.00)
Variance of demean firm effects				0.07 (0.18)
2 × Covariance worker-firm effects	0.08 (0.19)	0.08 (0.19)	0.08 (0.19)	0.08 (0.19)
Variance of residuals	0.05 (0.12)	0.05 (0.12)	0.05 (0.12)	0.05 (0.12)
Variance of group effects			0.00 (0.00)	0.00 (0.00)
2 × Covariance group-firm effects			0.00 (0.00)	0.00 (0.00)
2 × Covariance group-worker effects			0.00 (0.00)	0.00 (0.00)

Notes: This table presents the variance decomposition of worker earnings. Columns 1 and 2 presents the decomposition based on the model in equation (4.1), while columns 3 and 4 use equation (4.2) that adds a business group fixed effect. In all columns we present the decomposition of the residuals of earnings that take into account year effects and worker level characteristics.

Table 10: Effect of Entering a Business Group

	(1)	(2)	(3)	(4)
	Log average earnings		Earnings std dev	
Post × Entering Group	0.022	0.027	0.019***	0.024**
	(0.018)	(0.020)	(0.007)	(0.011)
Observations	8,629	1,206	8,629	1,206
R-squared	0.964	0.978	0.855	0.945
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Strata-Year FE	Yes	Yes	Yes	Yes
Mean DV	7.079	7.261	7.079	7.261
SD DV	0.456	0.492	0.456	0.492

Notes: The dependent variable is the logarithm of the average earnings in the firm (columns 1 to 2) and the standard deviation of the logarithm of earnings (columns 3 to 4). Columns 1 and 3 use all controls, while columns 2 and 4 use the best control. The sample includes three years around the transition. *Entering Group* is a dummy that takes the value one for firms that entered into a business group. *Post* is a dummy that takes the value one from the year of transition and after for treated firms and their controls. All regressions include firm fixed effects and strata-year fixed effects. Robust standard errors are clustered at the firm level.

Table 11: Effect of Entering a Business Group by Decile

	(1) All	(2) 0-10	(3) 10-20	(4) 20-30	(5) 30-40	(6) 40-50	(7) 50-60	(8) 60-70	(9) 70-80	(10) 80-90	(11) 90-100
Panel A: Log wages all workers											
Post × Entering Group	0.022	-0.025	-0.006	0.001	0.006	0.011	0.022	0.020	0.012	0.028	0.040*
	(0.018)	(0.025)	(0.021)	(0.020)	(0.020)	(0.019)	(0.019)	(0.021)	(0.022)	(0.022)	(0.021)
R-squared	0.964	0.921	0.935	0.946	0.951	0.955	0.959	0.960	0.960	0.958	0.948
Panel B: Log wages incumbents											
Post × Entering Group	0.015	0.002	0.003	-0.002	-0.004*	0.000	0.004	-0.001	-0.006	-0.002	0.016
	(0.018)	(0.013)	(0.003)	(0.002)	(0.002)	(0.002)	(0.004)	(0.003)	(0.005)	(0.004)	(0.010)
Observations	8,626	7,282	7,373	7,697	7,811	7,970	8,085	8,106	8,173	8,154	8,252
R-squared	0.962	0.974	0.997	0.999	0.999	0.999	0.999	0.999	0.998	0.997	0.963
Panel C: Log employment											
Post × Entering Group	0.173**	-0.021	0.027	0.064	0.020	0.019	0.058	0.078	0.111	0.110	0.173*
	(0.075)	(0.107)	(0.089)	(0.077)	(0.089)	(0.078)	(0.080)	(0.078)	(0.091)	(0.093)	(0.095)
R-squared	0.901	0.800	0.812	0.817	0.826	0.828	0.837	0.836	0.837	0.832	0.843
Observations	8,630	8,630	8,630	8,630	8,630	8,630	8,630	8,630	8,630	8,630	8,630
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Strata-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is the logarithm of the average wage within the decile of the wage distribution before the transition (Panel A), the logarithm of the average wage for workers that were part of the firm before the transition (incumbents) within the decile of the wage distribution before the transition (Panel B), and the logarithm of employment within the decile of the wage distribution before the transition (Panel C). The sample includes three years around the transition. *Entering Group* is a dummy that takes the value one for firms that entered into a business group. *Post* is a dummy that takes the value one from the year of transition and after for treated firms and their controls. All regressions include firm fixed effects and strata-year fixed effects. Robust standard errors are clustered at the firm level.

Table 12: Effect of Entering a Business Group on Wage by Deciles for Entrants

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	All	0-10	10-20	20-30	30-40	40-50	50-60	60-70	70-80	80-90	90-100
Entering Group	0.119***	0.066**	0.021	0.058*	0.049	0.036	0.035	0.026	0.034	0.057	0.084***
	(0.038)	(0.033)	(0.033)	(0.033)	(0.034)	(0.034)	(0.035)	(0.038)	(0.037)	(0.035)	(0.031)
Observations	5,148	4,658	4,581	4,615	4,592	4,620	4,621	4,616	4,565	4,552	4,677
R-squared	0.589	0.615	0.666	0.695	0.689	0.680	0.699	0.680	0.707	0.728	0.702
Strata-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is the logarithm of the average wage for entrants over incumbents within the decile of the wage distribution before the transition. The sample includes data from the year of transition up to three years after. *Entering Group* is a dummy that takes the value one for firms that entered into a business group. The set of baseline controls include the logarithm of the total employment of the firm, average tenure of workers, the share of female workers, and the workers' average age and standard deviation. All regressions include strata-year fixed effects. Robust standard errors are clustered at the firm level.

Table 13: Heterogeneous Effects by Business Group Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
	Log avg earnings			St dev log earnings		
	Family	# Firms	# Employees	Family	# Firms	# Employees
Business group × Z	-0.055	0.002	0.007	0.018	-0.001	-0.012**
	(0.042)	(0.001)	(0.021)	(0.012)	(0.000)	(0.005)
Business group	0.390***	0.313***	0.330***	0.039***	0.060***	0.105***
	(0.030)	(0.041)	(0.098)	(0.008)	(0.012)	(0.026)
Observations	258,322	258,322	258,322	258,322	258,322	258,322
R-squared	0.305	0.305	0.305	0.139	0.139	0.139
Sector-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean DV	6.805	6.805	6.805	0.412	0.412	0.412
SD DV	0.520	0.520	0.520	0.160	0.160	0.160

Notes: The dependent variables are the logarithm of average earnings (columns 1-3) and the standard deviation of the logarithm of earnings (columns 4-6). *Business Group* is a dummy that takes the value one if a firm is part of a business group. *Family* is a dummy that takes the value one if the group is controlled by a family, *# firms* is the number of firms in the business group, and *# employees* is the total number of employees in the business group. The set of baseline controls include the logarithm of the total employment of the firm, average tenure of workers, the share of female workers, and the workers' average age and standard deviation. All regressions include sector-year fixed effects. Robust standard errors are clustered at the firm level.

A Online Appendix

A.1 Robustness

Table A.1: Robustness to Top-Coded Earnings

	(1)	(2)	(3)	(4)	(5)	(6)
	Log Average Earnings			Std Deviation of Log Earnings		
Business Group	0.354***	0.364***	0.031*	0.060***	0.063***	0.015**
	(0.023)	(0.023)	(0.017)	(0.006)	(0.006)	(0.006)
Log employment	0.074***			0.022***		
	(0.002)			(0.001)		
Observations	258,322	258,322	258,017	258,322	258,322	258,017
R-squared	0.316	0.320	0.949	0.143	0.147	0.834
Sector-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Employment centiles FE	No	Yes	No	No	Yes	No
Firm FE	No	No	Yes	No	No	Yes
Mean DV	6.704	6.704	6.704	0.417	0.417	0.417
SD DV	0.497	0.497	0.497	0.164	0.164	0.164

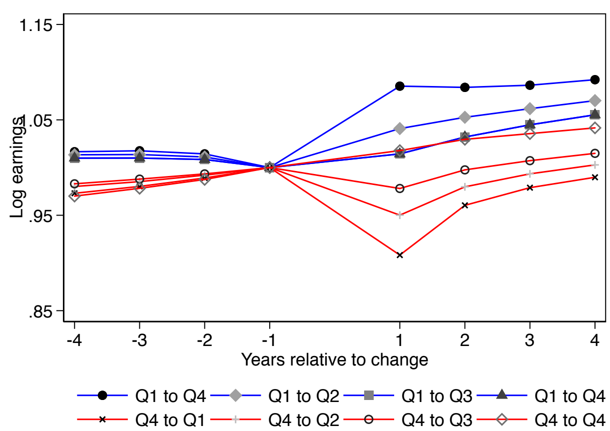
Notes: In columns 1 to 3 the dependent variable is the log of average earnings, while in columns 4 to 5 is the standard deviation of the logarithm of earnings. To construct both variables we first impute the value of earnings for workers that have top-coded earnings. We do this by parametrically estimating a tobit regression for the log earnings within a cell. We construct the cells using age brackets and gender. See Bonhomme and Hospido (2017) for more details on the imputation. *Business Group* is a dummy that takes the value one if a firm is part of a business group. *Log employment* is the logarithm of the total employment of the firm. The set of baseline controls include average tenure of workers, the share of female workers, and the workers' average age and standard deviation. Columns 2 and 4 add dummies for each centile of the empirical distribution of employment. Robust standard errors are clustered at the firm level.

A.2 Robustness to AKM model

We now present two robustness exercises for the AKM model proposed by Card, Heining, and Kline (2013). First in figure A.1 we present the average log earnings for switchers for years around the switch. We divide the switchers depending on the quartile of the firm FE at which they were before and after the change, e.g. a switch *Q1 to Q4* means that the worker was in firm in the bottom quartile of the firm FE distribution and moved to a firm in the top quartile of the distribution. We scale the average log wage by the value in $t = -1$ so the values can be interpreted as changes with respect to wage before the switch. We find that there is a large increase in wages when workers switch from a Q1 firm to a Q4 firm and this increase is reduced monotonically if she moves to a Q3, Q2, or Q1 firm. On the other side for a worker switching from a Q4 firm to a Q1 firm there is a reduction in wages and this reduction is monotonically smaller if she moves to a Q2, Q3, or Q4 firm. Also the consistently with the AKM specification the gain from switching from a bottom to a top are similar to the losses from switching from a top to a bottom.

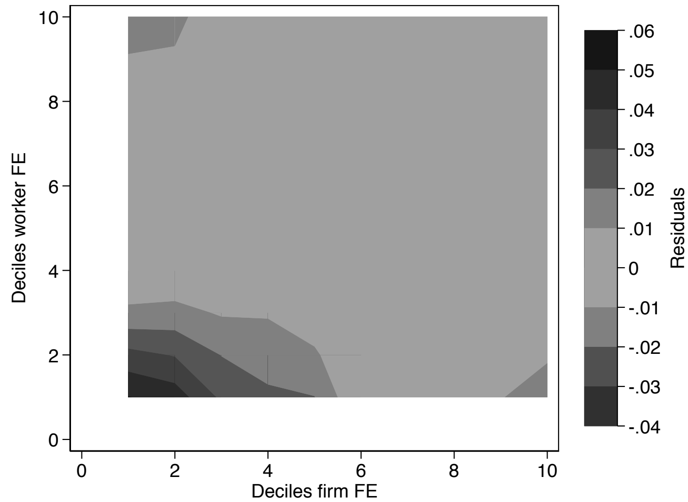
Then in figure A.2 we present the average of the AKM model residuals for different combinations of worker and firm FEs deciles. We find some evidence of misspecification for workers in the bottom deciles of worker and firm FE, since the errors show sistematically more positive values. The values are moderate and similar to the ones found in Alvarez, Benguria, Engbom, and Moser (2018) in these deciles for the Brazilian case. This is also consistent with Engbom and Moser (2017) who argue that this pattern is consistent with a binding minimum wage.

Figure A.1: Earnings evolution for switchers



Notes: This figure shows the evolution of log earning for switchers. The switches are divided depending on the quartile of the firm FE of the origin and destination firm, e.g. a switch *Q1 to Q4* means that the worker was in firm in the bottom quartile of the firm FE distribution and moved to a firm in the top quartile of the distribution. Average log earnings are normalized by the value in $t = -1$.

Figure A.2: Residuals



Notes: This figure shows the average residuals from the AKM model for each worker and firm FE deciles.

Table A.2: Frequency of Switchers

	All	Business-group	Stand-alone
Number of workers	7,447,093	409,248	7,037,845
Number of jobs per worker	2.57	3.69	2.50
	(1.78)	(2.12)	(1.58)
Share of switchers	0.64	0.85	0.62

Notes: This table presents the number of jobs per worker and the share of switchers in the sample. A switcher is defined as a worker who is associated with two or more jobs in our sample. The column *BG* shows the statistics for those workers that worked at least one year in a business group, while the column *Standalone* presents them for those who never worked in a group.

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