Ownership Networks and Labor Income*

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Abstract

We document a novel relationship between networks of firms linked through ownership (i.e., business groups) and labor income using matched employer-employee data for Chile. Business group affiliation is associated with higher wages, even after controlling for firm size and individual worker effects. The group premium is stronger for top workers; hence, group firms have higher wage dispersion. The premium remains present when comparing group firms and matched stand-alone firms, and in within-firm comparisons using transitions in and out of groups. Our results are consistent with workers reaching higher productivity and wages by leveraging their skills on the group's organizational structure.

JEL classifications: G32, J31

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1 Introduction

We study the impact of business groups –i.e., networks of multiple firms with a common controlling shareholder– on the labor income of their employees. Firms affiliated to business groups represent a large fraction of public firms in many emerging and developed markets (see Khanna and Yafeh 2007, and Morck, Wolfenzon, and Yeung 2005). There is evidence that firm value, financing policies, investment, and other firm-level outcomes are related to business-group affiliation. Given this evidence, it is natural to connect ownership structures with employee wages. Ownership refers to the control of real assets, and therefore it can affect worker productivity, incentives schemes, or perhaps the rent sharing between owners and workers. To the best of our knowledge, we are the first to conduct a systematic study of the wage differentials between employees in group and non-group (i.e., stand-alone) firms in the economy.

We use a matched employer-employee dataset that covers all formal employment in the Chilean economy over the years 2004-2016. Business groups are prevalent in Chile, as seen in Buchuk, Larrain, Munoz, and Urzúa (2014) and Aldunate, González, Prem, and Urzúa (2020). Through regressions of average employee earnings at the firm level onto a business-group indicator, we find that group firms pay 42% more than stand-alone firms. This is a novel finding that we label the "group premium." This result controls for observable dimensions of worker composition, industry-year fixed effects, and, crucially, for the total number of employees, given the association between wages and firm size (see Bloom, Guvenen, Smith, Song, and von Wachter 2018, Colonnelli, Tag, Webb, and Wolter 2018, and Song, Price, Guvenen, Bloom, and von Wachter 2018). The group premium is significant in all segments of the earnings distribution, but it is almost twice as large for workers in the top decile of the distribution compared to workers in the bottom decile. Therefore, business group firms have higher within-firm earnings dispersion than stand-alone firms.

The empirical strategy mentioned above exploits cross-firm variation to identify the effects of business group affiliation. Although we control for observable characteristics, our results could be explained by unobservable characteristics that correlate with group affiliation and lead to higher earnings. For example, group firms may operate in market segments that require high-productivity workers. These workers would earn higher wages in stand-alone firms anyway. In order to control for the unobservable elements of the worker force, we employ the methodology of Abowd, Kramarz, and Margolis (1999), henceforth AKM. This methodology, following the implementation suggested by Card, Heining, and Kline (2013), decomposes observed earnings into worker-specific, firm-specific, and time-specific effects. We can identify those terms because some workers move between firms in time (which identifies worker effects), and different workers work in the same firm at the same moment in time (which identifies firm effects). The worker fixed effects capture unobservable skills and other innate characteristics of a worker. In order to control for the time-varying composition of the labor force in each firm, we add the firm-level average of AKM worker effects to our previous regressions. We find that the group premium is reduced to about 11%, but it is still statistically significant. Therefore, group firms hire workers of higher skills, but this cannot fully account for the group premium.

Beyond the composition of the workforce, there might still be a selection of firms of specific characteristics into business groups, and these characteristics can be related to higher wages. For instance, export firms are high-productivity firms (Melitz and Redding, 2014), and such underlying productivity can drive both the selection into business groups and higher wages. In order to address this concern, and using the coarsened-exact-matching methodology (Iacus, King, and Porro, 2012), we construct a sample of stand-alone firms that match the business group firms in terms of industry, employment and payroll deciles, and listed status. We then compare wages in group firms to their matched stand-alone firms. We find that the group premium is reduced to close to 15%, but it is still statistically robust. Hence, even across firms in the same industry and with similar characteristics, we find that there is a group premium for workers.

Our next identification strategy takes advantage of the fact that some firms joined (or exited) business groups during the sample period. We can control for a host of unobservable firm characteristics by exploiting within-firm variation as the firm *changes* business group affiliation. When focusing on these transitioning firms, we find that the group premium is 3.7% and statistically significant. Interestingly, while the group premium in the bottom decile of workers is practically zero, the premium in the top decile is 5.3%. This again implies a relevant impact of business group affiliation on within-firm wage dispersion. We also combine the before-and-after methodology of transitioning firms with the previous matching methodology. We find that the group premium is still present, and the top-bottom wage difference is of a similar magnitude. Finally, we study workers who transition into business groups compared to workers who move to stand-alone firms. After controlling for worker fixed effects, we find that the group premium is also 3.7%.

Overall, we find that the group premium is a robust feature of the data with different and complementary empirical strategies. We cannot fully resolve the endogeneity of group structures, and hence the possibility that some omitted variable drives both the affiliation to business groups and wages. For instance, group transitions are not random. A firm might grow through a technological discovery that simultaneously attracts the interest of a business group and drives up wages. Although we control for worker effects, observable and unobservable (time-invariant) firm characteristics, industry-year fixed effects, and others, it is impossible to rule out such a case. Regardless of identification challenges, the fact that employees of group firms are paid higher wages, and that there is more wage dispersion in group firms, are still relevant empirical facts that can improve our understanding of both labor markets and business groups.

In terms of underlying mechanisms that can explain the link between groups and wages, our results are most consistent with workers reaching higher productivity and wages by leveraging their skills on the group's organizational structure. The literature on the organization of production shows that hierarchies are a way to multiply the impact of knowledgeable workers at the top (Garicano and Rossi-Hansberg, 2015). Consistent with this idea, we find that the wage premium is stronger in groups with multiple layers in the ownership structure (i.e., layers in the hierarchy), and when there are more employees in the top firm of the group. Groups may hire more skilled workers, as our results with the AKM worker effects suggest, but the organizational structure of groups also allows high-skill workers to be more productive. We find less evidence consistent with rent-sharing between owners and workers (Kline, Petkova, Williams, and Zidar, 2019), or with high-power incentives and tournament-like mechanisms (Lazear and Rosen, 1981). Although we cannot fully disprove these theories, our evidence suggests that the key for explaining the connection between groups and wages is in the hierarchy of control and the structure of decision-making in groups (Belenzon, Hashai, and Patacconi, 2019).

This paper makes a contribution, first and foremost, to the literature on business groups. The existence of business groups has been a long-standing puzzle, although there are advantages and disadvantages to these corporate structures (Khanna and Yafeh, 2007). Some authors point out that internal capital markets are an important financial advantage of business groups (see Almeida and Wolfenzon 2006, Gopalan, Nanda, and Seru 2007, 2014, and Belenzon, Berkovitz, and Rios 2013). In a related vein, group structures can reduce financial exposure by allocating risks into separate firms with limited liability (Belenzon, Lee, and Patacconi, 2022). On the negative side, some argue that the separation of control and ultimate ownership that occurs in groups' pyramidal structures provides bad incentives for controlling shareholders to abuse minority shareholders (see Bertrand, Mehta, and Mullainathan 2002, and Kandel, Kosenko, Morck, and Yafeh 2019). These theories deal with the costs and benefits of group structures that allocate control, capital, and risk. By providing a systematic comparison of the wages of group workers and stand-alone workers, our results illustrate the implications of such allocation mechanisms for labor compensation.

The recent literature on business groups has also pointed out that internal *labor* markets can be a source of competitive advantage (see Belenzon and Tsolmon 2016, and Faccio and O'Brien 2021). For example, business groups can ease the reallocation of top workers to booming sectors and firms (Huneeus, Larrain, Larrain, and Prem, 2021). Our study showcases another dimension of the interaction between business groups and labor. The results suggest that their organizational structure can increase the productivity of workers, as reflected in wage levels and dispersion. Our findings shed light on the organization of labor as another competitive advantage of business groups, beyond previously identified financial and strategic advantages.

Our paper also contributes to the literature on the role of firms on earnings inequality. Previous literature has focused on the relationship between inequality and firm size (Song, Price, Guvenen, Bloom, and von Wachter 2018; Mueller, Ouimet, and Simintzi 2017), 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 ownership structures can also influence earnings inequality, which is in line with the importance of ownership structures for other labor outcomes (e.g., the connection between private equity ownership and employment documented in Davis, Haltiwanger, Handley, Jarmin, Lerner, and Miranda 2014). The stronger group premium among top workers contributes to our understanding of the sources of inequality. It suggests that the increase of wages of top workers is not solely explained by their human capital (Bender, Bloom, Card, Reenen, and Wolter, 2018), but that the organizational structure of the firm can amplify innate differences in skill.

The remainder of the paper is structured as follows. Section 2 describes the data and presents summary statistics. Section 3 presents cross-sectional evidence on the effect of business groups on employee earnings. Section 4 exploits the transitions of firms and workers to identify the impact of groups on wages. Section 5 provides an overview of potential explanations. Section 6 concludes.

2 Data

We combine two data sources to study the connection between employee earnings and the ownership structure of firms. First, we use a matched employer-employee dataset. Second, we use a business-group dataset to link the firms in our sample according to their ownership structure.

2.1 Matched Employer-Employee Dataset

Chilean firms are required by law to pay a fraction of workers' monthly wages into an individual savings account and a common fund in case of unemployment. The unemployment insurance system is managed by a private entity, which keeps an administrative dataset. This unemployment insurance dataset reports the wage, at the monthly frequency, for each employer-employee relationship. Besides wages, firms report their main industry, and the gender and birth date of the worker.

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 10 workers in all years.

2.2 Business Group Dataset

Chilean listed firms are also required by law to report financial statements and ownership structures regularly to the local stock market regulator. 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). 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 (see Donelli, Larrain, and Urzúa 2013, and Larrain and Urzua 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 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. 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 network of firms –public and private– that make up each business group. 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 controlled by the Angelini family 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. The rest of the firms in the group are private firms.

We merge these datasets using the tax IDs of firms that appear in both data sources. To secure the privacy of workers and firms, we cannot observe the merged dataset. The Chilean internal revenue service requires all summary statistics and results that are reported to be calculated using at least 25 tax IDs.

Insert Figure 1 here

2.3 Summary Statistics

Table 1 reports summary statistics for our sample covering the period 2004-2016. Our sample includes 383 business-group firms (1% of total firms) and 35,027 stand-alone firms that are not affiliated to any group. The sample contains 99,996 workers in group firms (4% of total workers) and 2,336,445 workers in stand-alone firms. The average firm in our sample employs 122 workers. Group firms employ 3.7 times more workers than stand-alone firms (=435/118). Average tenure in stand-alone firms is 2.6 years, and it is slightly higher for group firms (2.92 years). The average worker is almost 38 years old, in group and stand-alone firms. The fraction of female workers is smaller in group firms (24%) than in stand-alone firms (34%). All these differences between group and stand-alone firms are statistically significant.

Insert Table 1 here

2.4 Inequality Between and Within Firms

In order to motivate the importance of firms for earnings inequality, we investigate the variance decomposition of Song, Price, Guvenen, Bloom, and von Wachter (2018). We decompose the overall cross-sectional variance of log earnings into a between-firm and a 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 $\overline{y}_{j,t}$ is the average earnings for firm j. After some algebra one can show that the overall variance can be decomposed into two terms:

$$\underbrace{\text{var}(y_{i,j,t})}_{\text{Overall dispersion}} = \underbrace{\text{var}(\overline{y}_{j,t})}_{\text{Between-firm dispersion}} + \underbrace{\sum \omega_j \times \text{var}(y_{i,j,t}|i \in j)}_{\text{Within-firm dispersion}}. \tag{2.1}$$

That is, dispersion in overall earnings can be decomposed into the between-firm dispersion of 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 (2.1) for each year between 2004 and 2016. Total 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.

Insert Figure 2 here

3 Cross-Sectional Evidence on Business Groups and Employee Earnings

This section is focused on cross-sectional regressions that show the effect of business group affiliation on employee earnings. Beyond standard controls, such as firm size, we show that group effects are robust to unobservable (although time-invariant) worker effects, and for firm-level matching based on observable characteristics. These do not exhaust all identification threats, but they show that the group effects are not simply capturing some other, more obvious, mechanisms.

3.1 Business Groups and Between-Firm Inequality

To study how business groups contribute to the between-firm component of earnings inequality, we regress log average firm earnings into a business group indicator variable:

$$\overline{y}_{j,t,s} = \beta BG_{j,t} + \gamma LogEmployment_{j,t} + \delta Controls_{j,t} + \psi_{t,s} + \epsilon_{j,t,s}, \tag{3.1}$$

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 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 the 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.

Insert Table 2 here

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 the same size, both with similar worker composition and operating in the same sector in the same year, the average earnings in the group firm are 42% higher than in 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 (3.1) for different segments of the within-firm earnings distribution. For example, in column (3) we focus on workers below the 10th percentile of the distribution; in column (4) we focus on workers between the 10th and 20th percentile, and so on. We observe a significant "group premium" in all segments of the earnings distribution. Moreover, the premium is monotonically increasing as we move towards top workers. The last column in Table 2 reports the wage differential between top-decile and bottom-decile workers. The group premium difference between top and bottom workers is close to 20%, and is highly significant.[1]

3.2 Business Groups and Within-Firm Inequality

We now estimate a regression similar to equation (3.1) using as a dependent variable the standard deviation of log earnings in a firm. In this specification, we also control for firm size, because recent work shows that large firms have high within-firm inequality (Mueller, Ouimet, and Simintzi, 2017). 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 amounts to 13% of earnings inequality in our sample (= 0.053/0.412). Column (3) controls for 100 firm-size buckets and the results remain unchanged.

Insert Table 3 here

As an alternative measure of within-firm inequality we use inter-decile ranges. Column (4) in Table 3 focuses on the earnings of the top 90th percentile relative to the bottom 10th percentile, column (5) compares the top 90th with the bottom 50th, and column (6) compares the top 50th with the bottom 10th. For all three cases, we observe that inequality is higher in group firms than in stand-alone firms. The last column with the 50-10 range implies that the effects are not driven exclusively by the very top workers (those at the top 90th percentile of the earnings distribution).[2]

3.3 Controlling for Unobservable Worker Effects

We use the methodology of Abowd, Kramarz, and Margolis (1999), AKM, to decompose observed earnings into worker-specific, firm-specific, and time-specific terms. We follow the implementation suggested by Card, Heining, and Kline (2013). We identify those terms by exploiting the fact that some workers move between firms in time (which identifies worker effects) and different workers work in the same firm at the same moment of

[1] Our results are robust to controlling for firm size in a non-parametric way, i.e., adding dummies for each one of the one hundred percentiles of the distribution of firm size (see Appendix Table A.1).

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

time (which identifies firm effects). In particular, we estimate the following model:

$$y_{i,j,t} = \theta_i + \phi_j + X'_{i,t}\Omega + \tau_t + \epsilon_{i,j,t}, \tag{3.2}$$

where $y_{i,j,t}$ 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., skills or 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. Table A.3 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.[3]

We retrieve the worker fixed effects from equation (3.2) and use the firm-level average or standard deviation of these fixed effects as controls to re-estimate regression (3.1). We report the results in Table 4. Column (1) reproduces the previous results for baseline comparison. Column (2) shows that the group premium remains highly significant but decreases in size to 11.5% or about 1/4 of the baseline effect. Columns (5) and (8) show that the effects of group affiliation on the standard deviation of earnings and the 90-10 inter-decile range are no longer significant after controlling for AKM effects. This shows that worker composition is different between business group and stand-alone firms and it explains an important part of the differences of earnings between these two types of firms. However, the general group premium survives this relatively strict control for worker composition.

Insert Table 4 here

[3]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 to the unobserved error component. We assess the validity of this assumption in several ways following Card, Heining, and Kline (2013), see Appendix A.2.

3.4 Controlling for Selection Bias with Matching

Affiliation to business groups is not random, hence the previous results are potentially biased due to a selection of firms into business groups. To partially address this selection problem, we implement the coarsened exact matching of Iacus, King, and Porro (2012). This methodology looks for stand-alone firms that are observationally equivalent to the group firms right before the moment of their affiliation to a group, so that all residual variation at that moment is random. We match each group firm with potential control firms according to several firm characteristics: industrial sector, deciles for the number of workers and total payroll, and whether the firm is publicly listed or not. Table 4 reports regression results within the sample of group firms and their matched stand-alone controls. Columns (3), (6), and (9) show that the effect of group affiliation on average earnings and earnings dispersion is highly significant, although the magnitude of the effects is reduced when compared to the baseline estimation. The group premium falls to 15.8% (column 3), which is similar to the reduction after AKM controls. Hence, the selection of firms into business groups based on observable characteristics can account for a part, but not all of the effect.

4 Transitions In and Out of Business Groups

4.1 Firm Transitions

The results in the previous section exploit cross-sectional variation to document a correlation between group affiliation and employee earnings. However, our results could be driven by unobservable characteristics that simultaneously lead to group affiliation and higher earnings on average (or higher dispersion). For example, group firms could be high-productivity firms (which is unobservable), and hence workers in these firms earn higher wages, but this would be the case regardless of ownership status. To provide further evidence that the link between group affiliation and earnings is indeed driven by ownership, we exploit the fact that some firms in our sample change their status from stand-alone to group firms and vice versa.

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. On average, there are 11 transitions per year, with a maximum of 30 in 2005 and a minimum of six in 2011 and 2013. Transitions are scattered across different business groups: there are four groups with more than 10 transitions, four groups with five to 10 transitions, and 12 groups with less than five transitions. Transitions are also scattered across sectors. Table A.4 presents summary statistics for entering firms the year before they join a business group. These firms tend to be smaller in terms of employment, they pay lower average wages, they have younger workers, and they have workers with lower tenure than the average firm in a group.

4.1.1 Panel Estimation with Firm Fixed Effects

We introduce firm fixed effects into our specification in equation (3.1) and therefore exploit within-firm variation in time: we compare the earnings of the same firm before and after a transition in or out of a group. 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 in that industry. If the industry is booming because of productivity growth, such growth could explain both the affiliation to the business group and the change in employee 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.[4]

Table 5 reports the results. Columns (1)-(2) focus on average earnings and columns (4)-(5) on the within-firm standard deviation of earnings. Column (1) shows that average earnings increase 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 (4) shows that joining a group increases the dispersion of earnings by 0.016, which represents a 3.9% increase with respect to the standard deviation in the sample (=0.016/0.412).

Insert Table 5 here

In order to refine the transition tests, in columns (2) and (4) we repeat the analysis including the firm-level average or dispersion of AKM worker effects as controls (like in Table 4). We estimate firm fixed effects from equation (3.2), 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 one firm before the transition and another firm after the transition. This means that we estimate two sets of fixed effects for firms that switch their affiliation. By combining the firm fixed effects strategy with the AKM adjustment, we can control for

[4] One potential concern with this two-way fixed effect approach is that the estimated coefficient can differ from the true ATT (average treatment effect for the treated) because of negative weights in individual ATTs. This happens because of treatment heterogeneity between late and early treated (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 coefficients, suggesting that this is a minor issue in our setting.

unobserved worker composition that changes over time. Admittedly, this might be over-controlling, but at the same time, it sets a high bar for the impact of group affiliation. The group coefficient for average earnings remains positive and significant (column 2), but the size of the effect is reduced to 1.3%. 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 change affiliation remains almost unchanged (column 5 compared to column 4).

4.1.2 Differences-in-Differences with Matched Sample

To partially address the selection of firms into business groups, we combine the previous transition test with the matching methodology discussed earlier. This matching is implemented in two rounds, with tighter bounds in the first round. In both rounds, we match each group firm with control (stand-alone) firms according to firm characteristics (i.e., sector, number of workers, total payroll, and a publicly-listed dummy). In the first round, we use deciles of the empirical distribution to create the strata. For example, if a firm that becomes affiliated with 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 stratum or cell 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 regression takes the form of a matching difference-in-differences:

$$y_{j,r,t} = \beta(Entry_j \times Post_{j,t}) + \alpha_j + \alpha_{r,t} + \epsilon_{j,r,t}, \tag{4.1}$$

where j, r, and t stand for firm, cell, and year, 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 of one after a firm enters a group or for its control firms in the same years. α_j and $\alpha_{r,t}$ are firm fixed effects and cell-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 of interest, measures the difference in outcome $y_{j,r,t}$ between firms that enter groups and stand-alone firms, before and after the transition, and controlling for fixed firm characteristics.

We find that, upon affiliation with a business group, firms increase the average wage by

2.2% (Table 5, column 3), but it is imprecisely estimated. The effect on wage inequality is larger and statistically robust. After affiliating with a group, firms experience an increase in wage inequality of 0.019 (columns 6), in line with our previous estimates. In Figure A.1 it can be seen that there are no parallel trends before affiliation for both outcome variables, thus supporting the use of our matching difference-in-differences as a plausible identification strategy.[5]

4.1.3 Changes in Earnings across the Wage Distribution

In Table 6 we conduct the previous analysis of transitioning firms for workers in different deciles of the wage distribution. With the panel regressions that include firm fixed effects (Panel A) we find that there is a strong increase in the average wage of workers in the top half of the wage distribution, but little or no change for workers in the bottom half. The top-bottom difference is 5.4% (column 11). Using the matching differences-in-differences regression (Panel B), we find a similar top-bottom difference of 6.4% (column 11). Hence, the group premium is also stronger for top workers if we narrow the identification strategy to firms that change their group affiliation.

Insert Table 6 here

4.2 Worker Transitions

We complement the previous analysis on firm transitions by looking at workers who join business group firms. The results are reported in Table 7. In particular, we analyze the earnings growth of a worker who moves from a stand-alone firm to a group firm, relative to a worker who moves from a stand-alone firm to a comparable stand-alone firm (matched to the group firm). The effect of moving to a group firm on earnings growth is 8.4% and highly significant (column 1). The effect increases in magnitude and remains highly significant after controlling for AKM worker effects (column 2), or standard worker controls (column 3). More importantly, the group premium is robust to adding worker fixed effects (column 4). The magnitude of the group premium is smaller in this last case

[5] This figure presents a dynamic version of equation (4.1):

$$y_{j,r,t} = \sum_{j=-3}^{J=3} \delta_k (Entry_j \times I[j = k]) + \alpha_j + \alpha_{r,t} + \epsilon_{j,r,t}, \tag{4.2}$$

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.

(3.7%), but for this estimation we focus attention on the within-worker effect for those workers with multiple transitions between firms. Results in Table 7 indicate that workers indeed receive higher earnings when they join a business-group firm.

Insert Table 7 here

5 Potential Explanations

In this section, we study mechanisms that can explain the effects of business groups on wages. We present tests based on the heterogeneity of our results across business groups and firms of different characteristics. In Table 8 we show results for regressions such as those in equation (3.1) but adding interactions of the business group indicator with group and firm characteristics (Z). The dimensions of heterogeneity that we employ are only proxies associated with different mechanisms, so they do not exhaust all possibilities. Although we cannot fully discard other theories, our results are most consistent with an explanation where groups allow workers to leverage their skills on the organizational structure and, hence, increase productivity and receive higher wages. This is particularly the case for top workers endowed with general or managerial skills, which are necessary to coordinate work in large hierarchies (Garicano and Rossi-Hansberg, 2015). Given the relevance of top workers, in addition to regressions for average firm-level wages (Panel A), we show separate regressions for the top decile of wages (Panel B).

Insert Table 8 here

5.1 Organizational Structure

As seen in Tables 4 and 7, skill differentials captured by AKM worker effects can account for a relevant fraction –but not all– of the wage gap between group and non-group workers. The AKM worker effects capture skills that are innate to the worker, or skills that we can identify separately from the firm in which each worker is employed. The group premium remains present after the inclusion of AKM worker effects, which implies that group firms pay higher wages not only because they attract naturally skilled workers. There is something in the match between the group firm and the worker that leads to higher wages. One possibility is that group firms make high-skill workers even more productive. The literature shows that there are network effects in the organization of work, in particular, production hierarchies increase the returns on the knowledge of top workers (see Garicano and Rossi-Hansberg 2006). Hence, the productivity of workers can be higher in a business group hierarchy that allows workers to leverage their innate skills.

It is not easy to bring this hypothesis to the data, but several group characteristics can proxy for the complexity of the organizational structure. For example, groups with more firms, employees, or sectors can multiply the impact of top workers. In a related vein, if there are more layers in the control hierarchy of the group (e.g., 4 layers of firms in Figure 1), then there is more space to leverage on the skills of top workers (Caliendo, Monte, and Rossi-Hansberg, 2015). The number of employees in the top firm of the ownership structure (e.g., Antarchile in Figure 1) can proxy for the amount of resources spent in coordinating the group's structure underneath.

In columns 1-5 of Table 8 we add interactions of the group dummy with these proxies for the organizational structure. The number of group firms and group employees (columns 1 and 2) have small effects and are not statistically significant. The interaction with the number of industrial sectors (column 3) is positive and statistically significant, but only for the average worker (Panel A) and not for workers in the top decile (Panel B). This can be consistent with the idea that groups and conglomerates help workers transfer to more productive sectors without depreciating their human capital (Tate and Yang, 2015). This effect seems to be less important for top workers who have more general skills and can easily transition to other sectors.

We find positive and significant interactions with the number of ownership layers (column 4) and the number of employees in the top firm (column 5). Both these effects are relevant for average workers (Panel A) and top workers (Panel B) alike. This evidence suggests that the group premium is related to the way in which production is organized (layers in the hierarchy), and the amount of resources spent in coordinating such organizational structure (workers at the top). Hence, the key for explaining the connection between groups and wages seems to be in the particular structure of control and decision-making of groups (Belenzon, Hashai, and Patacconi, 2019).

5.2 Incentives

We study two alternative hypotheses beyond the effects of the organizational structure. The first alternative hypothesis is related to the incentives provided by group firms. We need to think of incentives that apply to the entire organization and not only those linked to equity compensation. Those high-power incentives are relevant for a few top positions such as the CEO (Murphy 1999). Hence, it is unlikely that they can explain a widespread group premium on wages such as the one we document. For example, even the top decile of workers contains more than 40 employees in the average group firm.

One 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 top-workers should have higher wages in groups with more firms and employees. As already seen in columns 1-2 of Table 8, this is not the case in our sample.

Other theories argue that incentives can be derived from comparisons across firms within the group. Large within-group differences can be considered unfair and reduce employee motivation and retention (Ederer and Patacconi, 2010). In this case, incentives are provided by paying employees in lower-tier group firms wages more commensurate with those of firms higher up in the organizational hierarchy. In order to bring this hypothesis to the data we study whether the group premium depends on the position of the firm in the control structure and on the size of the firm. In column 6 of Table 8 we find that the interaction of the group dummy and the indicator for top firm is negative, i.e., the group premium is larger for lower-tier firms. The effect is, however, only marginally significant for the average worker (Panel A), and not significant for top workers (Panel B). We then interact the group dummy with an indicator for the largest firm within the group in terms of number of employees. The largest firm is typically not the firm at the top of the control structure, but a productive firm in the middle of the structure (e.g., Arauco in Figure 1). In column 7 we find that this interaction is negative and strongly significant for top workers and for the average worker. This result suggests that smaller group firms receive a larger wage premium, which is consistent with the existence of cross-firm incentives within the group.[6] At the same time, it is also consistent with the implications of the organizational theory. In fact, layers (firms) with more employees are lower in the hierarchy and receive lower wages (Garicano and Rossi-Hansberg, 2015).

[6]The group premium for large firms is still positive as indicated in column 7 of Table 8 by the sum of the interacted and un-interacted coefficients (0.172=-0.275+0.447).

5.3 Rent-Sharing

The fact that the group premium cannot be fully explained by skill differences (AKM worker effects) may also imply that there is rent-sharing between owners and workers (Kline, Petkova, Williams, and Zidar, 2019). Some of the wage differential can simply be rent extraction due to agency problems with top management (Bebchuk, Fried, and Walker 2002). However, the presence of strong controlling shareholders in business groups sheds doubts on that interpretation. Similarly, rent-sharing may be a sign of nepotism (Pérez-González 2006). However, the presence of a group premium on entire cohorts of workers suggests that pure nepotism is unlikely to explain the results. Perhaps some family members and friends are among top employees in group firms, 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 is 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 bring this idea to the data we split business groups into those with a family as controlling shareholder and those with other controlling shareholders (e.g., foreign multinationals, the state, etc.). We see in column 8 of Table 8 that the interaction of the group dummy with family ownership is negatively related to average earnings (Panel A) and the earnings of top workers (Panel B). However, the effect is not statistically significant. Contrary to the paternalistic hypothesis, there is little evidence of more rent-sharing among family groups compared to other groups.

Overall, although incentives and rent-sharing may play a role, the results are most consistent with the organizational structure of business groups as the driver of wage differentials. Groups organize production in a way that allows more knowledgeable workers to leverage their skills on the group's hierarchy. This increases productivity and wages, particularly at the top of the wage distribution, which contributes to within-firm inequality.

6 Conclusions

We document a novel relationship between networks of firms linked through ownership (i.e., business groups) and labor income using matched employer-employee data for Chile in the period 2004-2016. We show that business group affiliation is associated with higher wages, even after controlling for firm size and individual worker effects. Although it is reduced, the group premium in wages remains present in comparisons between group firms and matched stand-alone firms, and in within-firm comparisons using transitions in and out of groups. We find a similar premium for workers transitioning from stand-alone to group firms. Our results show that the group premium is stronger for workers at the top of the earnings distribution, which implies that group firms have higher within-firm earnings dispersion.

In terms of mechanisms, our results are most consistent with workers reaching higher productivity and wages by leveraging their skills on the group's organizational structure. In particular, the wage premium is stronger in business groups with more layers in the ownership structure, and in groups with more employees in the top firm. The layers of the hierarchy are related to the way in which production and the decision-making process are organized. The employees at the top proxy for the amount of resources employed in coordinating the group's activity.

Our findings shed light on the organization of labor as another competitive advantage of business groups, beyond previously identified financial and strategic advantages. Our evidence also contributes to our understanding of the role of firms for earnings inequality, and in how different organizational structures can amplify innate differences in worker skills.

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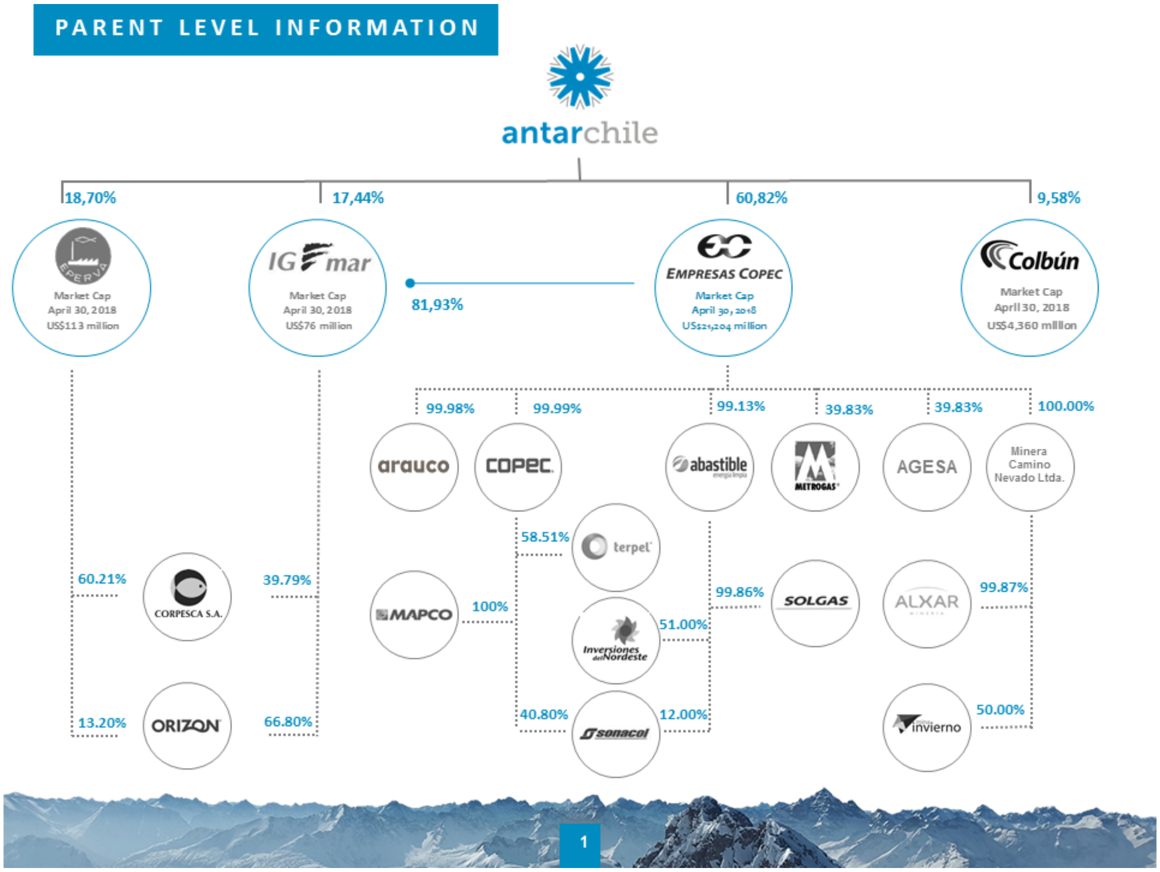
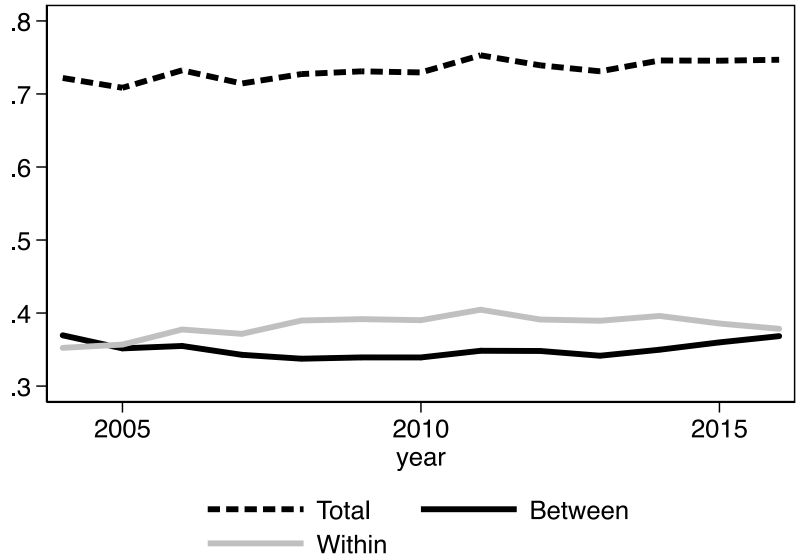
Figure 1: Example of Business Group Ownership Structure: Antarchile



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 total, between-firms, and within-firm earnings dispersion as presented in equation (2.1).

Table 1: Summary Statistics

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

Notes: This table presents averages of different variables for business-group and stand-alone firms. Standard deviations are presented in parentheses, and p-values are reported in brackets.

Table 2: Business Group Affiliation and Average Earnings

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	All		0-10	10-20	20-30	30-40	40-50	50-60	60-70	70-80	80-90	90-100	Top-bottom
Business Group		0.427***	0.290***	0.323***	0.349***	0.374***	0.398***	0.423***	0.446***	0.474***	0.499***	0.494***	0.205***
		(0.025)	(0.023)	(0.025)	(0.026)	(0.027)	(0.028)	(0.029)	(0.030)	(0.030)	(0.029)	(0.026)	(0.019)
Log employment	0.076***	0.071***	0.031***	0.049***	0.054***	0.058***	0.061***	0.066***	0.074***	0.083***	0.098***	0.119***	0.091***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
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	258,322
R-squared	0.228	0.236	0.235	0.255	0.248	0.242	0.241	0.244	0.244	0.241	0.233	0.219	0.161
Sector-Year FE	Yes	Yes	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 (columns 1 and 2), the logarithm of the average earnings in decile $[j, j+10]$ for $j = [0, 10, 20, 30, 40, 50, 60, 70, 80, 90]$, and the difference between the top decile and the bottom decile (column 13). *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 includes average tenure of workers, the share of female workers, and workers' average age. Robust standard errors are clustered at the firm level.

Table 3: Business Group Affiliation and Within-firm Inequality

	(1)	(2)	(3)	(4)	(5)	(6)
	Std Deviation of Log Earnings			Inter-decile range		
				90-10	90-50	50-10
Business Group		0.053***	0.056***	0.637***	0.176***	0.221***
		(0.006)	(0.006)	(0.065)	(0.026)	(0.026)
Log employment	0.021***	0.020***		0.155***	0.055***	0.038***
	(0.001)	(0.001)		(0.007)	(0.003)	(0.003)
Observations	258,322	258,322	258,322	258,322	258,322	258,322
R-squared	0.134	0.135	0.138	0.147	0.077	0.156
Sector-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean DV	0.412	0.412	0.412	2.925	1.660	1.729
SD DV	0.160	0.160	0.160	1.492	0.552	0.598

Notes: In columns 1 to 3, the dependent variable is the standard deviation of the logarithm of earnings, while in columns 4 to 6, the dependent variable is the ratio of the average wages in the decil j over the average the wages 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 includes 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. The last two lines report the mean and standard deviation of the dependent variable (DV) for each column.

Table 4: Controlling for AKM Worker Effects and Firm Matching

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Log average earnings			Std Deviation of Log Earnings			Inter-decile range: 90-10		
	Baseline	AKM	Matching	Baseline	AKM	Matching	Baseline	AKM	Matching
Business Group	0.427***	0.115***	0.158***	0.053***	-0.006	0.023***	0.637***	-0.025	0.260***
	(0.025)	(0.009)	(0.021)	(0.006)	(0.007)	(0.006)	(0.065)	(0.064)	(0.068)
Observations	258,322	258,320	79,393	258,322	258,320	79,393	258,322	258,320	79,393
R-squared	0.236	0.800	0.574	0.135	0.451	0.221	0.147	0.455	0.227
Sector-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Matching-cell FE	No	No	Yes	No	No	Yes	No	No	Yes
Mean DV	6.805	6.805	7.043	0.412	0.412	0.458	2.925	2.925	3.293
SD DV	0.520	0.520	0.506	0.160	0.160	0.130	1.492	1.492	1.430

Notes: In columns 1 to 3, the dependent variable is the logarithm of the average earnings in the firm, in columns 4 to 6, the dependent variable is the standard deviation of the logarithm of earnings, while in columns 7 to 9, the dependent variable is the inter-decile range between the top and bottom deciles. In columns 2, 5, and 7, we add as covariates the average and the standard deviation of worker fixed effects respectively, estimated from equation (3.2). In columns 3, 6, and 9, the sample includes firms that are part of a business group for at least one year and their set of control firms. We construct the matching controls using Iacus, King, and Porro (2012) coarsened exact matching, using as matching characteristics the deciles of employment and payroll, the sector, and a dummy for whether the firm is publicly listed. Columns 3, 6, and 9 add fixed effects for each matching cell (group firm together with control firms). *Business Group* is a dummy that takes the value one if a firm is part of a business group. The set of baseline controls includes 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 5: Business Group Transitions

	(1)	(2)	(3)	(4)	(5)	(6)
	Log average earnings			Std Deviation of Log Earnings		
Estimation:	Firm Fixed Effects		Matching-DID	Firm Fixed Effects		Matching-DID
Business Group	0.037**	0.013*		0.016***	0.014**	
	(0.015)	(0.007)		(0.006)	(0.006)	
Post × Entering Group			0.022			0.019***
			(0.018)			(0.007)
Observations	258,017	258,015	8,629	258,017	258,015	8,629
R-squared	0.950	0.973	0.964	0.829	0.847	0.855
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector-Year FE	Yes	Yes	No	Yes	Yes	No
AKM Controls	No	Yes	No	No	Yes	No
Cell-Year FE	No	No	Yes	No	No	Yes
Mean DV	6.806	6.806	7.079	0.412	0.412	0.485
SD DV	0.520	0.520	0.456	0.160	0.160	0.100

Notes: In columns 1 to 3, the dependent variable is the logarithm of the average earnings in the firm, while in columns 4 to 6, the dependent variable is the standard deviation of the logarithm of earnings. In columns 2 and 4, we add as covariates the average and the standard deviation of worker fixed effects respectively, estimated from equation (3.2). *Business Group* is a dummy that takes the value one if a firm is part of a business group. The set of baseline controls includes average tenure of workers, the share of female workers, and workers' average age and standard deviation. In columns 3 and 6, we estimate a matching difference-in-differences model. To do this, we construct the matching controls using Iacus, King, and Porro (2012) coarsened exact matching based on the characteristics before the transition: the deciles of employment and average payroll, the sector, and a dummy for whether the firm is publicly listed. *Entering Group* is a dummy that takes the value one for firms that entered a business group. *Post* is a dummy that takes the value one from the year of transition and after for treated firms and for their control firms. Columns 3 and 6 add matching cell-year fixed effects. All regressions include firm fixed effects and sector-year fixed effects. Robust standard errors are clustered at the firm level.

Table 6: Business Group Transitions and Earnings by Decile

	(1) 0-10	(2) 10-20	(3) 20-30	(4) 30-40	(5) 40-50	(6) 50-60	(7) 60-70	(8) 70-80	(9) 80-90	(10) 90-100	(11) Top-Bottom
Panel A: Firm Fixed Effects											
Business Group	-0.001	0.015	0.023	0.032*	0.035*	0.043**	0.038**	0.039**	0.045**	0.053***	0.054***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.020)	(0.019)	(0.015)	(0.018)
Observations	258,017	258,017	258,017	258,017	258,017	258,017	258,017	258,017	258,017	258,017	258,017
R-squared	0.855	0.904	0.919	0.926	0.931	0.937	0.941	0.942	0.938	0.922	0.816
Sector-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Matching-DID											
Post $\times$ Entering Group	-0.025	-0.006	0.001	0.006	0.011	0.022	0.020	0.012	0.028	0.040*	0.064***
	(0.025)	(0.021)	(0.020)	(0.020)	(0.019)	(0.019)	(0.021)	(0.022)	(0.022)	(0.021)	(0.024)
Observations	8,629	8,629	8,629	8,629	8,629	8,629	8,629	8,629	8,629	8,629	8,629
R-squared	0.921	0.935	0.946	0.951	0.955	0.959	0.960	0.960	0.958	0.948	0.855
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cell-Year FE	Yes	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 $j = [0, 10, 20, 30, 40, 50, 60, 70, 80, 90]$ and the difference between the top decile and the bottom decile (column 11). *Business Group* is a dummy that takes the value one if a firm is part of a business group. In Panel A, the set of baseline controls includes the logarithm of the total employment of the firm, average tenure of workers, the share of female workers, and workers' average age and standard deviation. In Panel B, we estimate a matching difference-in-differences model. To do this, we construct the matching controls using Iacus, King, and Porro (2012) coarsened exact matching based on the characteristics before the transition: the deciles of employment and average payroll, the sector, and a dummy for whether the firm is publicly listed. *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 for their control firms. All columns in panel B add matching cell-year fixed effects. Robust standard errors are clustered at the firm level.

Table 7: Earnings Growth of Workers Joining Business Groups

	(1)	(2)	(3)	(4)
	Earnings growth			
Business Group	0.084***	0.078***	0.077***	0.037***
	(0.023)	(0.023)	(0.019)	(0.013)
Observations	2,489,486	3,688,694	2,510,300	2,489,486
R-squared	0.020	0.029	0.031	0.484
Sector-Year FE	Yes	Yes	Yes	Yes
Worker controls	No	No	Yes	No
AKM Worker FE	No	Yes	Yes	No
Worker FE	No	No	No	Yes
Mean DV	0.207	0.226	0.229	0.207
SD DV	0.544	0.572	0.579	0.544

Notes: The dependent variables is the growth in earnings around a transition from one firm to another at the worker level. We only focus on transition from non-business group firms. The sample includes firms that were part of a business group for at least one year and their set of controls. We construct the matching controls using Iacus, King, and Porro (2012) coarsened exact matching, using as matching characteristics the deciles of employment and payroll, the sector, and a dummy for whether the firm is publicly listed. Business Group is a dummy that takes the value one if a firm is part of a business group. The set of workers controls include a dummy for female workers and the workers' average age. The AKM controls includes the worker fixed effect, estimated from equation (3.2). Robust standard errors are double-clustered at the firm and worker level.

Table 8: Heterogeneous Effects by Business Group and Firm Characteristics

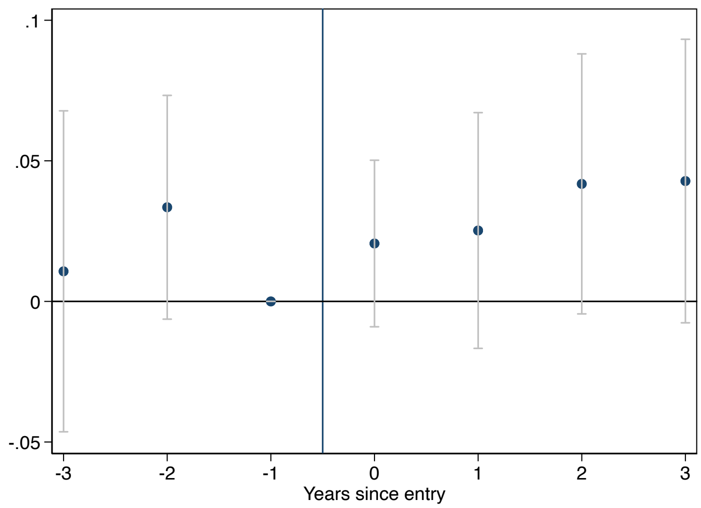
	(1) Group # Firms	(2) Group # Employees	(3) Group # Sectors	(4) # of ownership layers	(5) Employment firm at the top	(6) Firm at the top	(7) Largest firm	(8) Family group
Panel A: Log avg earnings								
Business group × Z	0.003	0.010	0.017**	0.054***	0.016*	-0.119*	-0.275***	-0.070
	(0.002)	(0.023)	(0.008)	(0.020)	(0.009)	(0.070)	(0.090)	(0.048)
Business Group	0.367***	0.381***	0.427***	0.428***	0.427***	0.532***	0.447***	0.461***
	(0.046)	(0.107)	(0.025)	(0.025)	(0.025)	(0.066)	(0.026)	(0.033)
R-squared	0.236	0.236	0.236	0.236	0.236	0.236	0.236	0.236
Mean DV	6.805	6.805	6.805	6.805	6.805	6.805	6.805	6.805
Panel B: Top decile								
Business group × Z	0.002	-0.009	0.010	0.049**	0.020**	-0.091	-0.304***	-0.041
	(0.002)	(0.023)	(0.008)	(0.021)	(0.009)	(0.066)	(0.098)	(0.050)
Business Group	0.455***	0.540***	0.498***	0.498***	0.498***	0.578***	0.520***	0.518***
	(0.050)	(0.108)	(0.026)	(0.026)	(0.026)	(0.062)	(0.027)	(0.035)
R-squared	0.214	0.214	0.214	0.214	0.214	0.214	0.214	0.214
Mean DV	7.267	7.267	7.267	7.267	7.267	7.267	7.267	7.267
Observations	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
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variables are the logarithm of average earnings in Panel A and the logarithm of average earnings for the top decile of wage earners in Panel B. *Business Group* is a dummy that takes the value one if a firm is part of a business group. We interact *Business Group* with different group and firm characteristics (Z) defined at the top of each column. *Group # firms* is the number of firms in the business group, *Group # employees* is the total number of employees in the business group, *Group # sectors* is the number of different sectors in the group, *# of ownership layers* is the number of ownership layers in the group, *Employment firm at the top* is the number of employees in the firm that is at the top of the group's ownership structure, *Firm at the top* is a dummy that takes the value one if the firm is at top of the group's ownership structure, and *Largest firm within the group* is a dummy that takes the value one if the firm is the largest in terms of employees within the business group, *Family group* is a dummy that takes the value one if the group is controlled by a family. The set of baseline controls includes the logarithm of the total employment of the firm, average tenure of workers, the share of female workers, and workers' average age. All regressions include sector-year fixed effects. Robust standard errors are clustered at the firm level.

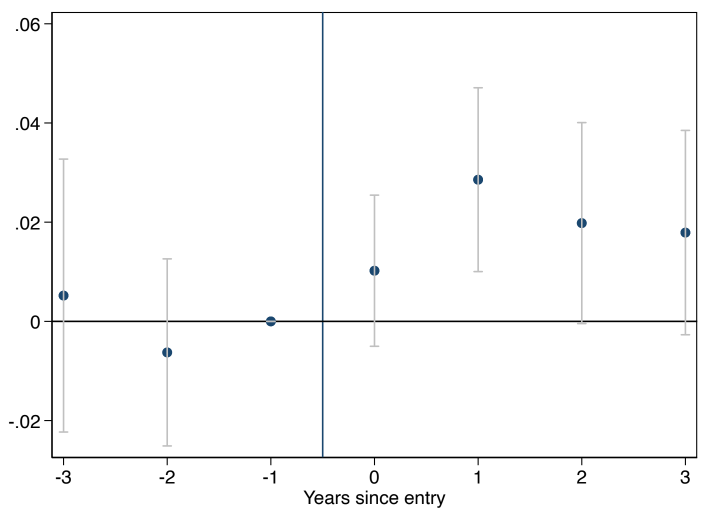
A Online Appendix

A.1 Robustness

Figure A.1: Dynamic Effects of Entering a Business Group



A. Pay premium



B. SD earnings

Notes: This figure present the coefficients from specification (4.2). Confidence intervals at 95% are presented in gray lines.

Table A.1: Business Group Affiliation and Average Earnings: Adding employment centile fixed effects

	(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	(12) Top-Bottom
Business Group	0.436***	0.293***	0.328***	0.355***	0.381***	0.406***	0.431***	0.456***	0.485***	0.513***	0.510***	0.217***
	(0.025)	(0.023)	(0.024)	(0.026)	(0.027)	(0.028)	(0.029)	(0.029)	(0.029)	(0.028)	(0.025)	(0.019)
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
R-squared	0.239	0.240	0.259	0.251	0.245	0.244	0.247	0.248	0.245	0.238	0.226	0.171
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	Yes	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 (columns 1), the logarithm of the average earnings in decile $[j, j+10]$ for $j = [0, 10, 20, 30, 40, 50, 60, 70, 80, 90]$, and the difference between the top decile and the bottom decile (column 12). *Business Group* is a dummy that takes the value one if a firm is part of a business group. The set of baseline controls includes average tenure of workers, the share of female workers, and workers' average age. We also include fixed effects by the centile in the empirical distribution of firm level employment, Robust standard errors are clustered at the firm level.

Table A.2: Robustness to Top-Coded Earnings

	(1)	(2)	(3)	(4)	(5)	(6)
	Log Average Earnings			Std Deviation of Log Earnings		
Business Group	0.418***	0.426***	0.032*	0.067***	0.070***	0.015**
	(0.027)	(0.026)	(0.017)	(0.006)	(0.006)	(0.006)
Log employment	0.063***			0.021***		
	(0.003)			(0.001)		
Observations	258,322	258,322	258,017	258,322	258,322	258,017
R-squared	0.239	0.242	0.949	0.136	0.139	0.833
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 includes average tenure of workers, the share of female workers, and workers' average age. Columns 2 and 4 add dummies for each centile of the empirical distribution of employment. Robust standard errors are clustered at the firm level.

Table A.3: 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.

Table A.4: Summary Statistics for Firms Transitioning to Business Groups

	(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

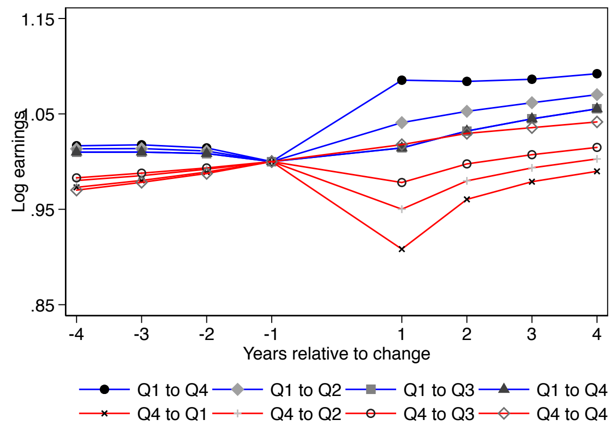
Notes: This table presents summary statistics for firms transitioning to business groups in the year before the transition.

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.2 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.

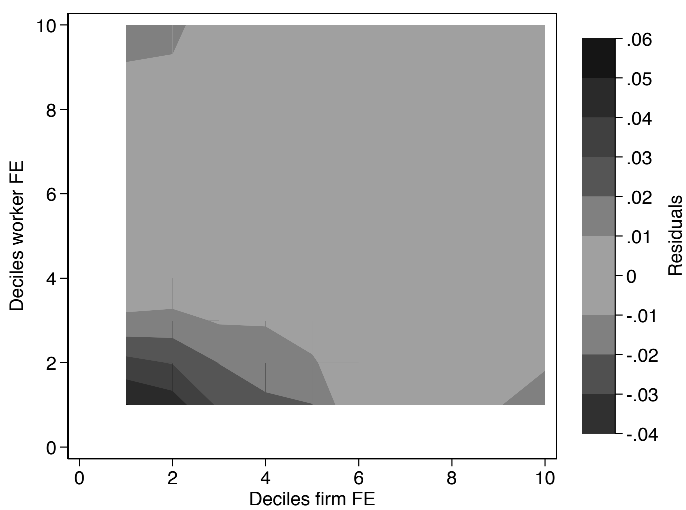
Then, in Figure A.3 we present the average of the AKM model residuals for different combinations of worker and firm FEs deciles. We find some evidence of misspecification for workers in the bottom deciles of worker and firm FE, since the errors show systematically more positive values. The values are 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.2: 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 a 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.3: Residuals



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

A.3 Augmented AKM model

We also consider the augmented AKM model where we add group effects (γ_g):

$$y^r_{i,j,t} = \theta_i + \phi_j + \gamma_g + \xi_{i,j,t}, \tag{A.1}$$

where $y^r_{i,j,t}$ is the residual of worker earnings once the age polynomial and year effects from (3.2) 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:

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

Besides the variance of each element, the covariances are interesting in capturing 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 with strong business groups.

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

$$\begin{aligned} var(y^r_{i,j,t}) = {} & var(\theta_i - \bar{\theta}_{j,t}) + var(\xi_{i,j,t}) + var(\bar{\theta}_{j,t}) + var(\phi_j - \bar{\phi}_{g,t}) + var(\bar{\phi}_{g,t}) \\ & + var(\gamma_g) + 2cov(\theta_i, \phi_j) + 2cov(\theta_i, \gamma_g) + 2cov(\phi_j, \gamma_g), \end{aligned} \tag{A.3}$$

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 (A.3) 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 A.5. 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).

Table A.5: 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 (3.2), while columns 3 and 4 use equation (A.1) 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. Percentages of total variance are presented in parentheses.