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## **LABOR MARKET CONCENTRATION AND EARNINGS:**

EVIDENCE FROM CHILE

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## LABOR MARKET CONCENTRATION AND EARNINGS: EVIDENCE FROM CHILE<sup>1</sup>

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### Abstract

This paper studies the effect of labor market concentration on earnings in Chile over 2005-2019. The paper has three main results. First, it documents a negative relationship between local employment concentration and firms' average wages. Second, it shows that labor market concentration affects more negatively the earnings of high-wage workers. As a result, within-firm earnings dispersion declines with employment concentration. Finally, it shows that workers' earnings are affected differently by employment concentration depending on their employers' degree of product market power—measured in terms of price-cost markup. The paper finds a more moderate negative effect of labor market concentration on workers' earnings in high-markup firms. This result suggests that high-markup firms use their higher rents in more concentrated labor markets both to retain and attract more productive, high-skill workers.

Códigos JEL: D24, E24, J21, J24, J31, J54

Keywords: Earnings, monopsony power, labor market concentration, market power, Chile

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## 1. Introduction

A growing body of research shows that economic concentration has risen globally over the last decades (Autor et al., 2020; De Loecker & Eeckhout, 2018). A lot of attention has been given to the causes and consequences of concentration in *output* markets. However, economic concentration in *input* markets can also have substantial effects on welfare. One market where this connection is especially clear is the labor market. Concentration in the labor market erodes competition between employers, increasing their ability to set wages below the level that would prevail under perfect competition. Recent evidence confirms this, providing consistent evidence that wages are lower in more concentrated U.S. labor markets (Azar et al., 2020; Benmelech et al., 2020; Rinz, 2020, among others). Nevertheless, there is still incomplete understanding about whether this relationship holds more generally—especially in developing countries—and whether high product market power firms set wages differently than comparable, low market power firms.

In this paper, we study the relationship between labor market concentration and wages. For this purpose, we use a rich administrative employer-employee dataset for Chile that contains information for the universe of formal firms and workers. Notably, the dataset allows us to construct highly disaggregated local labor concentration measures. Evidence for the United States shows that the bulk of workers seek jobs locally (Manning & Petrongolo, 2017; Marinescu & Rathelot, 2018). Accordingly, we exploit employment concentration differences across narrowly defined industries and geographic areas to identify the relationship between concentration and wages.

We begin by documenting the trajectory of aggregate employment concentration in Chile since 2005. To measure employment concentration, we focus on the widely used Herfindahl-Hirschman Index (*HHI*). While the *HHI* is subject to criticisms—see Syverson (2019) for a discussion—we choose to use it as our baseline measure of employment concentration because it allows direct comparison of our results with other studies. Consistent with evidence for the United States, we find that the aggregate employment *HHI* remained relatively stable over 2005-2019 (see Benmelech et al., 2020). The average employment-weighted *HHI* computed over 4-digit ISIC industries and municipalities was 0.410 in 2005, smoothly declined to 0.386 by 2011, and increased again to 0.415 by 2019. Nevertheless, despite its aggregate stability, we find that the *HHI* varies considerably across local markets.

Next, we turn to study the relationship between employment concentration and wages. When estimating it with Ordinary Least Squares (OLS), we find a non-robust coefficient on employment concentration that varies from positive to negative in our preferred specification. This surprising result is partially explained by the endogeneity of the *HHI*; its variation responds in part to supply and demand shocks that also affect wages.<sup>1</sup> To address the endogeneity of the *HHI*, we follow Azar et al. (2020) and implement a Two-Stages Least Squares (2SLS) strategy using the average employment-weighted *HHI* in other municipalities for the same industry and year as an instrument. When using the instrument for the *HHI*, we find a robust negative relationship between employment concentration and average wages. In quantitative terms, we obtain a reasonable response of wages; the results suggest that

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<sup>1</sup>This result is reminiscent of Rinz (2020), who find a positive relationship between average wages and employment concentration in OLS regressions for the United States. Similarly, Autor et al. (2020) reports a positive relationship between wages and product market concentration in the U.S.

an increase of one standard deviation in the *HHI* (0.324) reduces average earnings by 2.2 percent. This value is higher than comparable evidence for the United States by Rinz (2020), who finds that a similar change would lead to a decline in wages of only one percent.

We also show that the effect of employment concentration varies depending on the type of worker. High-wage workers (arguably) have more substantial bargaining power with the firm than low-wage workers. On the other hand, minimum wage regulations counterbalance firms' monopsony power over low-wage workers (Krueger, 2018) and low-wage workers have a broader range of outside options (including the possibility of transitioning to the informal market) because their skills are less sector-specific. On balance, it is unclear *a priori* whether the negative impact of employment concentration on wages should hold homogeneously across worker types. Using the richness of the Chilean data, we investigate which effect dominates, deriving different percentiles of the wage distribution within firms and finding a more substantial impact over high-wage workers. Indeed, low-wage workers are not significantly affected by labor market concentration. Ultimately, the differential impact of employment concentration over the distribution of wages results in a compression of wages and a decrease in earnings dispersion within firms.

Finally, we show that the negative effect of labor market concentration on workers' earnings varies depending on their employers' product market power. Following De Loecker et al. (2020), we proxy product market power with the firms' markup—a measure of their ability to charge prices above the marginal cost. As is well known, markups are endogenous; by definition, markups increase as firms decrease their expenditure in variable inputs, including labor. To address markups' endogeneity, we instrument firm-level markups with the revenue-weighted average markup charged by all other firms operating in the same 4-digit industry but located in different municipalities. Across specifications, we find a positive interaction term between labor market concentration and markups; higher markups lessen—although they do not overturn—the negative effect of labor market concentration on average wages. This result is consistent with recent evidence by Macaluso et al. (2019) for the United States, suggesting that high-markup firms exploit their advantageous hiring position in concentrated labor markets by hiring “better,” high-wage workers.<sup>2</sup>

Our paper contributes to the literature on the effect of labor market concentration on wages, providing the first evidence from a developing economy. Benmelech et al. (2020), Azar et al. (2020), Rinz (2020) and Qiu and Sojourner (2019) address the same question for the United States using national datasets. A robust finding in these studies is that employment concentration and wages are negatively related, as we find in our paper. We also use a large administrative dataset covering a large fraction of the formal Chilean economy and define employment concentration at the level of local markets. We contribute to this literature in two ways. First, we show that employment concentration has a stronger negative impact on high-wage workers' earnings, ultimately reducing within-firm wage dispersion. Second, we show that the earnings of workers employed in high market power firms are less impacted by employment concentration. This last finding contributes more generally to understanding the consequences of market power.

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<sup>2</sup> An alternative, non-competing explanation is that in more concentrated labor markets, firms use their market power to extract rents and share them with their workers.

The remainder of the paper is organized as follows. Section 2 presents a conceptual framework to derive the hypotheses that we later test with the Chilean data. Section 3 discusses the main features of the data, and then proceeds to analyze the aggregate evolution of earnings dispersion and market power in Chile since 2005. Section 4 discusses the main empirical specifications. Section 5 presents the empirical results. Finally, section 6 discusses the implications of our study and routes for future research.

## 2. Conceptual Framework

In this section, we discuss the relationship between labor market concentration and workers' earnings. This discussion will guide the derivation of the hypotheses that we later test using the Chilean data. We postpone the exposition of the specific empirical specifications until section 4.

First, labor market concentration can negatively affect workers' earnings in the presence of imperfect competition in the labor market.<sup>3</sup> Market power affects the balance of power between firms and workers, affecting the process of rent sharing. To the extent that labor market concentration reflects leading hiring positions, dominant firms enjoy a greater ability to set wages, and as a result, pay lower wages. Benmelech et al. (2020), Azar et al. (2020) and Rinz (2020) provide evidence for this mechanism, showing that in the United States, wages tend to be lower in areas where hiring is more concentrated.<sup>4</sup> Along the same lines, Webber (2015) finds that firms that face a more inelastic labor supply pay lower wages, suggesting that they exploit their monopsony power. We summarize this mechanism in the following hypothesis:

### **Hypothesis 1. Firms operating in more concentrated labor markets pay lower wages.**

It is worth mentioning that Hypothesis 1 is a conditional prediction; it does not preclude the possibility that firms pay higher wages in more concentrated labor markets, which can occur, for instance, if firms in these markets are more productive or if they have a different composition of their labor force. However, it does require that if there exist two comparable firms whose only difference is the employment concentration of the market in which they operate, the firm located in the more concentrated labor market should pay lower wages. We control for differences in firm and market characteristics in the empirical specifications, including a rich set of fixed effects and control variables.

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<sup>3</sup> Manning (2011) offers a revision of this literature. Imperfect competition can arise because of monopsony power in the labor market—either because workers prefer certain jobs or because employers have a dominant hiring position—or because in the presence of search frictions, firms pay less than the value of the marginal product of labor, extracting a higher fraction of rents. As Manning (2011) discusses, both models generate similar implications for wages and firms' characteristics, because both imply an upward-sloping labor supply function. More recently, Card et al. (2018), Lamadon et al. (2019) and Benmelech et al. (2020) study welfare implications of imperfect competition in the labor market.

<sup>4</sup> Autor et al. (2020) find an insignificant relationship between changes in concentration and changes in average wages in the United States. However, their evidence is limited to the manufacturing sector and does not necessarily reflect trends at the national level.

While hypothesis 1 refers to the effect of monopsony power in the labor market on average wages, it is silent about its impact on the within-firm earnings distribution. Unfortunately, there is no clear-cut prediction about the differential effect that labor market concentration exerts on earnings distribution. Nevertheless, we identify two possible mechanisms.

First, let us assume that workers' bargaining power correlates with their type: high-wage workers capture a relatively higher fraction of the surplus of their relationship with the firm than low-wage workers. This may arise because firms have to make worker-specific investments when hiring high-wage workers, perhaps because they need to carry out more complex tasks. Low-wage workers' skills, in contrast, tend to be less sector-specific—they perform a higher fraction of routine tasks that can be trained on-the-job. As a consequence, high-wage workers should capture a higher fraction of the relationship surplus than low-wage workers, so their salaries should be relatively less affected by labor market concentration, increasing the within-firm earnings distribution.

However, a second countervailing force can affect earnings dispersion, making the wage of low-wage workers less affected by employment concentration. The existence of minimum wage regulations limits the extent to which firms can reduce the earnings of low-wage workers in more concentrated labor markets. Thus, even if firms use their monopsony power to pay lower wages, we would observe a more negative relationship between wages and employment concentration for high-wage workers, leading to a fall in within-firm earnings dispersion<sup>5</sup>. In view of these possibilities, we outline the following null hypothesis:

**Hypothesis 2. Labor market concentration affects high- and low-wage workers' earnings similarly. As a result, within-firm wage dispersion does not change with labor market concentration.**

Even though Hypothesis 2 is somewhat conservative, its rejection provides specific information on the mechanism driving the relationship between earnings dispersion and employment concentration. In particular, if the more substantial bargaining power of high-wage workers drives the data, we would expect a positive relationship between employment concentration and wage dispersion. In contrast, if minimum wage regulations lead to a more nuanced reaction of low-wage workers' salaries, we would expect a negative relationship between employment concentration and wage dispersion.

Finally, we have a particular interest in understanding how product market power mediates the relationship between employment concentration and earnings. Recent literature provides evidence of a negative relationship between firms' labor share—defined as the ratio of wage bill to firm revenues—and markups, a measure of firms' market power. As De Loecker et al. (2020) discuss, high-markup firms naturally spend less on flexible inputs, such as labor, leading mechanically to a negative relationship between markups and the labor share. Autor et al. (2020) provide evidence for the United States and a sample of OECD countries, suggesting that globalization and technological change could be the driving force behind this relationship, leading to the emergence of mega-firms.

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<sup>5</sup> For reference, in 2020 the minimum wage in Chile was about US\$450 per month. This is almost twice as large as the minimum wage in Argentina, Colombia, Peru, and Mexico.

Although the negative relationship between markups and the labor share follows by construction, its relationship with average wages is less straightforward. A simple accounting exercise reveals that the low labor share in high-markup firms is either due to low average wages or a lower payroll. Only in the former do we expect a negative relationship between markups and average wages, as the lower labor share in the latter case is driven by employment. However, it is also possible that market power affects the composition of the firms' labor force. For instance, the model by Chade and Eeckout (2020) suggests that an increase in production complementarities—perhaps driven by technological change—could lead industry leaders to more aggressively hire high-skilled workers, leading them to obtain higher markups<sup>6</sup>. Under this mechanism, we would expect a positive relationship between wages and markups<sup>7</sup>.

How does product market power interact with labor market concentration to affect wages? We hypothesize that high market power firms have an incentive to cut salaries by less than their competitors, perhaps sharing a larger fraction of their rents with their employees. This way, they keep the more capable employees working in their firms, allowing them to maintain their market power. Thus, while we expect a negative relationship between employment concentration and wages (hypothesis 1), this relationship should be differentially less negative for high-markup firms. We summarize this discussion in the following hypothesis:

**Hypothesis 3. The negative effect of employment concentration on wages is relatively weaker in firms with high product market power.**

To sum up, while labor market concentration and earnings may be related through many different mechanisms, our discussion reveals that we expect a negative relationship between these variables in the vast majority of them. A proper understanding of which mechanism operates in the data requires analyzing this relationship using disaggregated, relationship-level data. We explain this in more detail in section 4, where we present the empirical specifications we exploit in the main econometric analysis. The next section presents the data we use and discusses the evolution of labor market concentration in Chile.

## 3. Data and Key Variables

### 3.1. Data sources

The paper employs two primary datasets to study the relationship between labor market power and earnings. These datasets include different pieces of information for the universe of Chilean firms and workers and are collected by the Chilean Tax Administration (*Servicio de Impuestos Internos, SII*) for the period 2005-2019. This section reviews key features of the data and describes the sample we use in the analysis.

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<sup>6</sup> According to this mechanism, the increase in production complementarities leads to more positive sorting from workers to firms and because high-wage workers are increasingly likely to be together. But this is correlated with markups because winning teams tend to obtain—at least to some extent—monopoly power.

<sup>7</sup> Note that the underlying mechanism that moves wages is quite different in this case. Average wages may vary even if the wage of existing workers does not change.

The first dataset exploits worker-level information from tax form 1887. The dataset covers the universe of formal employment and is available at the annual level. For each employer-employee pair, the dataset provides information on annual earnings and the months where the labor relationship was active. Each employee and firm have a unique individual identifier that is maintained throughout the sample<sup>8</sup>.

We complement the employment records from tax form 1887 with balance-sheet information from tax forms 22 (Annual Income Statement) and 29 (Monthly Value-Added Tax). These datasets contain detailed information of firm characteristics, such as sales, spending on raw materials, wage bills and fixed assets. It also provides information for the sector in which the firm operates (at the 4-digit ISIC level), and the municipality where the firm is located.<sup>9</sup> The SII tracks firms with the same identifier used in the worker-level dataset, form 1887. This allows us to combine both datasets to produce a rich employer-employee panel that covers the universe of formal workers and firms from 2004 to 2019.

To ensure a consistent dataset, we follow several steps. First, we drop observations with zero or missing information for fixed assets, sales, material expenditures or employment. Second, we follow Song et al. (2019) and focus on individual-year pairs with a strong attachment to the labor market. Consequently, we drop all individual-year pairs where the employee works less than three consecutive months in a year or earns less than the minimum wage. Third, for each year, we only consider the main occupation of the individual—defined as the highest salary job—and correct their annual income by adding their earnings from all occupations held in that year. Fourth, we drop firms hiring one worker at most throughout the sample to exclude self-employment. Finally, we drop firms from regulated sectors or with high government involvement (public sector, utilities, health and education) because firms’ wage structures may reflect non-market forces, and agriculture and personal services because there is a higher fraction of temporal and informal workers.

### 3.2. Labor market concentration and earnings

The paper uses the Herfindahl-Hirschman Index (*HHI*) as the main measure of labor market concentration. The *HHI* is widely used as a measure of market concentration, with higher values indicating more concentrated markets. Our definition of markets considers both geography and industry of occupation. In particular, we define markets at the municipality-industry-year level, with industries defined at the 4-digit ISIC level as in Benmelech et al. (2020) and Azar et al. (2020)<sup>10</sup>. Formally, the employment-*HHI* for industry *j* operating in municipality *m* at year *t* is defined as:

$$HHI_{mjt} \equiv \sum_{f=1}^F s_{fjt}^2 \quad (1)$$

<sup>8</sup> The tax identifier is unique, personal and non-transferable (anonymized by SII to comply with statistical secrecy requirements) and is assigned to natural persons when they are born and to firms at the time of their creation.

<sup>9</sup> The data define a firm’s location by the address of its headquarters. This data limitation will most likely bias our results against finding a negative relationship between wages and employment concentration because the headquarters offices tend to be located in larger cities. This will raise employment concentration in larger cities, where wages tend to be higher.

<sup>10</sup> We also run the analysis defining industries at the 6-digit ISIC level. As expected, labor market concentration is considerably higher, with a large fraction of markets—over 50 percent—with *HHI* equal to 1.0, indicating that a single firm employs all workers in these markets. Thus, we focus on markets defined at the 4-digit ISIC level, as we believe this is a more conservative definition. Nevertheless, results are quantitatively similar when using the more disaggregated market definition.



where  $s_{fjmt} \equiv l_{fjmt} / \sum_f l_{fjmt}$  corresponds to the employment market share of firm  $f$  operating in market  $mjt$ , and  $l_{fjmt}$  denotes the employment of firm  $f$ .

Our primary outcome variable is the log of the average wage per worker at the firm-year level. We also use other moments from the within-firm wage distribution. In particular, we compute the 10<sup>th</sup>, 25<sup>th</sup>, 50<sup>th</sup>, 75<sup>th</sup> and 90<sup>th</sup> percentiles of individual wages within firms and the standard deviation of individual earnings within firms. In all regressions, we control for labor productivity, computed as annual value-added divided by the number of workers employed by the firm.

### 3.3. Product Market Power

A growing body of evidence shows that product market power and economic concentration have risen globally (De Loecker & Eeckhout, 2018; De Loecker et al., 2020). Thus, we later aim to study whether high market power firms transfer their rents differently to workers in more concentrated labor markets. An important conceptual point is that, although labor market concentration and product market power are usually correlated, they do not have to be. This may occur if the industry operates under monopolistic competition (firms are small employers and yet enjoy product market power) or if workers tend to favor working in particular occupations (labor market power may arise without product market power).

To measure product market power, we follow De Loecker and Eeckhout (2018) and use firm-level markups—a measure of whether firms can charge prices above their marginal cost—as a proxy of market power. We derive markups by following the production-based approach popularized by De Loecker and Warzynski (2012). This method is flexible regarding the underlying demand structure and only requires production data. The main insight of this methodology is that the price-cost markup of a firm can be computed as the ratio between two elements: (i) the output elasticity of the firm with respect to any flexible input, and (ii) the expenditure share of the flexible input  $V$  (relative to sales). To derive markups, we consider materials as the relevant flexible input to compute markups. We will briefly explain how we compute each of these elements and relegate technical details to appendix A.

To estimate the production function coefficients, we specify a Cobb-Douglas production function, with labor, capital and materials as production inputs. Ideally, both inputs and outputs should be measured in terms of physical units to avoid the so-called input and output price bias (see De Loecker & Goldberg, 2014 for a detailed discussion). Unfortunately, we do not observe prices in our dataset. Therefore, we follow an alternative approach based on De Loecker (2011) and proxy for prices by introducing a standard horizontal differentiation demand system with constant elasticity of substitution (CES) for each industrial sectors. To estimate the coefficients, we follow the methodology proposed by Akerberg et al. (2015) to control for the endogeneity of firms' inputs choice and for the selection induced by non-random exits.

The second component needed to compute markups is the expenditure share, which is observed at the firm-level. We compute this element by dividing the value of material inputs expenditures by total firm-revenues. Once we have computed the value of materials' output elasticity ( $\alpha_M$ ) and its expenditure share ( $(P_{it}^M M_{it} / P_{it} Q_{it})$ ), we compute markups ( $\mu$ ) for firm as:

$$\mu_{it} = \alpha_M \times \left( \frac{P_{it}^M M_{it}}{P_{it} Q_{it}} \right)^{-1} \quad (2)$$

### 3.4. Summary Statistics

Table 1 shows descriptive statistics for the main firm characteristics and the baseline measure of labor concentration at the market level. The data has information for 1,319,102 firm-year pairs over the period 2004-2019. The average firm reports sales for a value of 2.1 billion pesos (US\$4.3 million in 2013 dollars), employs 36 workers and pays an annual wage of 4.3 million pesos (about US\$8,700 in 2013 dollars). All variables are positively skewed, with average values substantially above the respective median. For instance, the median firm reports sales of only 147 million pesos (US\$300,000 in 2013 dollars) and pays an annual wage of 2.6 million pesos (US\$5,300 in 2013 dollars).

Next, we discuss descriptive statistics for the baseline measure of local labor market concentration. Across all markets and years, the average employment *HHI* is 0.689, with a standard deviation of 0.324. The high value of the *HHI* follows mostly from a large number of markets with an *HHI* equal to 1.000. Indeed, about 43 percent of the markets we studied are dominated by a single employer. However, these markets tend to be relatively small. Indeed, when we weigh markets by their aggregate employment, the average *HHI* falls to 0.396.

**Table 1.** Summary Statistics

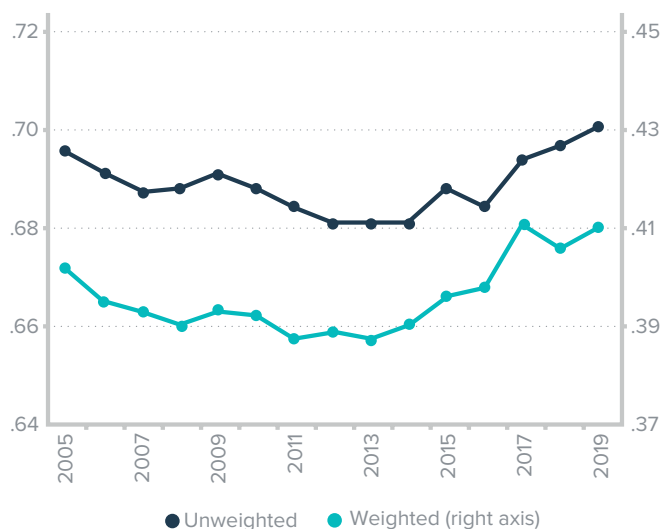
	Mean	Std. Dev.	Percentiles					Obs.
			10	25	50	75	90	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<b>Firm Characteristics</b>								
Sales	2,110	47,800	20	52	147	466	1,650	1,319,102
Employment	36	239	2	3	7	17	49	1,319,102
Average wage per worker	4.3	5.9	1.0	1.7	2.6	4.8	8.9	1,319,102
<b>Labor Market Concentration</b>								
Employment <i>HHI</i>	0.689	0.324	0.208	0.398	0.763	1.000	1.000	224,106
Employment <i>HHI</i> =1	0.435	0.496	0.000	0.000	0.000	1.000	1.000	224,106

Notes: The table lists the summary statistics for the variables used in the paper's baseline analysis sample. It comprises an employer-employee panel dataset for the universe of formal Chilean workers and firms over the period 2005-2019. The Herfindahl-Hirschmann Index (*HHI*) is computed using firms' employment shares over all firms in each 4-digit industry-municipality-year. All nominal variables are expressed in millions of 2013 Chilean pesos.

Figure 1 plots the evolution of the employment *HHI* over 2005-2019. On average, labor market concentration remained relatively stable over the period<sup>11</sup>. It slightly decreased from 0.696 in 2005 to 0.681 to 2014 (0.401 to 0.389 when weighting by employment). This trend reversed over the next four years, increasing to 0.701 in 2019 (0.410 when weighting by employment).

<sup>11</sup> This is consistent with evidence for the United States. Benmelech et al. (2020) show that the employment-weighted *HHI*—computed over 4-digit industry and commuting zones—increased no more than 3.2 percent in the U.S. manufacturing sector during 1978-2016.

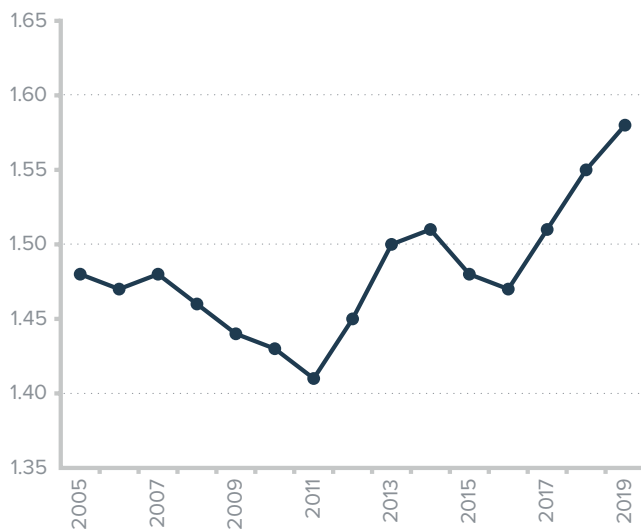
**Figure 1.** Evolution of the Employment *HHI* in Chile, 2005-2019



Notes: The figure shows the evolution of the *HHI* in Chile since 2005. The solid blue line (left axis) takes simple averages of the *HHI* across markets in each year. The dashed gray line weights the *HHI* by the employment of each market. We define markets at the level of 4-digit ISIC industries and municipalities.

Finally, figure 2 shows the evolution of average markups from 2005 to 2019. As with the case of employment *HHI*, the aggregate markup remained relatively stable over the period, with a slight increase from 1.47 in 2005 to about 1.57 in 2019. These results contrast with results in De Loecker and Eeckhout (2018), who report a decrease in aggregate markups starting in 1980 for the Chilean manufacturing sector.

**Figure 2.** Evolution of Markups in Chile, 2005-2019



Notes: The figure shows the evolution of the average (employment-weighted) markups in Chile since 2005. Markups are computed at the firm-level following De Loecker and Warzynski (2012).

## 4. Empirical Approach

This section presents the main empirical specifications, discusses threats to identification and introduces the instrumental variable approach.

### 4.1. Empirical Specifications

To test whether employers in more concentrated markets pays lower wages, we run two main specifications. First, we study how the level of labor market concentration relates to average wages. We test this hypothesis by estimating the following baseline regression for each firm  $f$  located in municipality  $m$  operating in industry  $j$  at year  $t$ :

$$\log \bar{y}_{fjst} = \beta_1 HHI_{mjt} + \beta_2 X_{fjst} + \delta_{mj} + \delta_{mt} + \delta_f + \varepsilon_{fjst} \quad (3)$$

where  $\bar{y}_{jst} \equiv \frac{1}{N_j} \sum_{i \in j} y_{ijst}$  denotes average earnings, computed across all workers employed in firm  $j$  at time  $t$ ,  $\delta_{mj}$  are market fixed effects,  $\delta_{mt}$  are municipality-year fixed effects,  $\delta_f$  are firm fixed effects and  $X_{jst}$  are firm-level controls. Controls include variables that affect the firms' labor demand, such as the logarithm of labor productivity (e.g., value-added per employee). We include municipality-year fixed effects to control for local shocks, and municipality-industry fixed effects (at the 4-digit level) to control for average differences in market. Our preferred specification includes firm fixed effects, which control for average differences in the workforce composition across firms. The coefficient of interest in regression (3) is  $\beta$ , which we expect to be negative<sup>12</sup>. In all specifications, we cluster standard errors at the 4-digit industry-municipality level, corresponding to the level at which the  $HHI$  varies.

The second main empirical specification seeks to determine whether firms exert their monopsony power homogeneously across worker types. To test this, we replicate (3) but use different percentiles of the within-firm log earnings distribution as dependent variables. The null hypothesis is that labor market concentration affects all workers similarly. Thus, we will reject the null if we find different coefficients  $\beta$  across wage percentiles. This can occur, for example, if high-wage workers have greater bargaining power than low-wage workers when setting wages with employers. In this case, we expect a more negative coefficient as we move to the bottom of the earnings distribution. But the opposite can also happen. Because the skills of low-wage workers tend to be less specific, they can move more easily across industries. Consequently, the wage of these workers could be less affected by the degree of employer concentration of a particular industry. In this case, we expect a more negative coefficient for high-wage workers.

<sup>12</sup> Our results consider municipalities—the lowest administrative division in Chile—as the relevant labor market. In most cases, municipalities include a single urban area, mapping well with the concept of commuting zones. However, the largest urban areas in Chile—such as the capital city of Santiago—include several municipalities. Using municipalities to define the  $HHI$  most likely biases our results towards a more positive relationship between labor concentration and wages because average wages are higher in larger cities.

## 4.2. Identification and IV Estimation

The main threat for identification in specification (3) is that changes in the  $HHI$  are endogenous. As Rinz (2020) discusses, demand and supply shocks affect wages and employer concentration simultaneously, biasing the OLS coefficient in opposite directions. Indeed, a positive labor demand shock increases average wages and decreases labor market concentration if the greater demand induces the entry of new firms. Conversely, positive labor supply shocks decrease average wages and decrease employers' concentration as smaller firms can expand their workforce with no need to compete with large firms. While labor demand shocks generate a downward bias in the OLS coefficients, labor supply shocks work in the opposite direction, biasing the OLS estimates upward.

### 4.2.1. Instrumental Variable Estimation

While the inclusion of the exhaustive set of fixed effects (including municipality-year, sector-municipality and firm fixed effects) substantially lessens the endogeneity concerns of the  $HHI$ , we implement an IV strategy following Azar et al. (2020) and Rinz (2020). Specifically, we instrument the  $HHI$  with the average  $HHI$  in other municipalities for the same 4-digit industry and year. Thus, conceptually, the instrument exploits variation in employer concentration that is driven by changes in national-level concentration and not by market-specific changes. Formally, we define the instrument as:

$$\widehat{HHI}_{mjt} \equiv \sum_{m' \neq m} \sum_{f \in m'} \phi_{FM'JT} HHI_{m'jt} \quad , \text{ with } \phi_{fm'jt} \equiv \frac{l_{fm'jt}}{\sum_{f \in m'} l_{fm'jt}} \quad (4)$$

For the baseline specification (3), the IV strategy works as follows. In the first stage, we predict market  $HHI$  based on the leave-one-out  $HHI$  instrument:

$$HHI_{mjt} = \gamma_1 \widehat{HHI}_{mjt} + \gamma_2 X_{f_{mjt}} + \gamma X_{mjt} + \delta_{mj} + \delta_{mt} + \delta_f + \epsilon_{mjt} \quad (5)$$

In the second stage, we regress the log average wage earned by employees working in firm  $f$  in market  $m_j$  in year  $t$ ,  $\log \bar{y}_{f_{mjt}}$ , on predicted  $HHI$ ,  $\widehat{HHI}_{mjt}$ , firm labor productivity, and fixed effects:

$$\log \bar{y}_{f_{mjt}} = \beta_1 HHI_{MJT} + \beta_2 X_{f_{mjt}} + \delta_{mj} + \delta_{mt} + \delta_f + \epsilon_{f_{mjt}} \quad (6)$$

### 4.2.2. Exclusion Restriction and Identification

Equation (6) recovers the causal effect of labor market concentration under the assumption that the leave-one-out  $HHI$  instrument affects average wages only through its effect on  $HHI$ . We note that this assumption may fail if demand or supply shocks are correlated across markets. We account for this possibility by including municipality-year fixed effects in all specifications. This weakens the exclusion restriction to some extent, allowing aggregate shocks to be correlated as long as they are not sector specific.

### 4.3. Interactions with Product Market Power

To test whether labor market concentration affects workers differently depending on their employers' degree of product market power, we add interactions between employment *HHI* and firm-level markups:

$$\log \bar{y}_{fijt} = \beta_1 HHI_{mjt} + \beta_2 \log(\text{Markup}_{mjt}) + \beta_3 HHI_{mjt} \log(\text{Markup}_{mjt}) + \beta_4 X_{fijt} + \delta_{mj} + \delta_{mt} + \delta_f + \varepsilon_{fijt} \quad (7)$$

From our discussion in section 2, the coefficients on markups ( $\beta_2$ ) and its interaction ( $\beta_3$ ) with the *HHI* can be either positive or negative. High-markup firms, by definition, have a lower wage-bill relative to sales than low-markup firms. This can be due to high-markup firms paying low average wages, in which case we would expect a negative  $\beta_2$ . However, the low labor share could be due to firms employing relatively fewer workers per unit of output than other firms in the same market. If firms focus their hiring on relatively more productive, high-wage workers, we expect a positive  $\beta_2$ .

One concern for estimating specifications (7) through OLS is that both the *HHI* and markups are endogenous. Fortunately, unlike the case of the *HHI*—which we discuss above—in the case of markups, we can sign the bias of the OLS estimates. Firms that hire more productive workers pay higher wages and are more productive. If they face a downward sloping demand curve and have price-setting ability, the productivity advantage allows firms to charge higher markups. Thus, this productivity channel implies a positive correlation between markups and wages, generating an upward bias in the OLS estimates. A similar conclusion follows when analyzing other sources of bias. For instance, changes to the competition firms face may affect markups and wages simultaneously. More stringent competition leads firms to charge lower markups, decreasing the value of the marginal product of labor. This generally leads to lower average wages. As with the productivity channel, this demand effect implies a positive correlation between markups and wages, biasing the OLS coefficients upward.

To alleviate endogeneity concerns, we instrument firm-level markups with the revenue-weighted average markup charged by all other firms operating in the same (4-digit) industry, but located in different municipalities. More concretely, for each firm *f* operating in industry *j* and municipality *m* at time *t*, we define the instrument as:

$$\widetilde{\text{Markup}}_{fijt} \equiv \sum_{m' \neq m} \sum_{f \in m'} \pi_{f m' jt} \text{Markup}_{m' jt} \quad , \text{ with } \pi_{f m' jt} \equiv \frac{r_{f m' jt}}{\sum_{f \in m'} r_{f m' jt}} \quad (8)$$

where *r* denotes firm revenues. Note that (8) excludes the markups from all firms operating in the same municipality from the computation of the average industry-level markup. Thus, the instrument captures markup variation originated by factors affecting the competitors of firm *f* in other markets.

## 5. Results

### 5.3.1. OLS Results

Table 2 presents OLS results from estimating the baseline wage equation (3). All regressions include labor productivity as a control to address the concern that results reflect variation in firms' productivity. Columns 1 to 3 report unweighted results, while column 4 weights observation by firm employment. All regressions control for labor productivity to exploit the variation of average wages that is unrelated to differences in labor productivity. As expected, across specifications, we find a positive and statistically significant coefficient on labor productivity, suggesting that firms with more productive workers pay higher wages.

**Table 2.** Labor Market Concentration and Wages: OLS Results Regressions

	(1)	(2)	(3)	(4)
Dependent variable:	$\log \bar{y}_{fmit}$	$\log \bar{y}_{fmit}$	$\log \bar{y}_{fmit}$	$\log \bar{y}_{fmit}$
<i>HHI</i>	.0539*** (.00719)	.0400*** (.00710)	-.0466*** (.00578)	-.0458*** (.0140)
ln(labor productivity)	.231*** (.00296)	.231*** (.00297)	.0831*** (.00139)	.0863*** (.00408)
Weighted	no	no	no	Employment
Year FE	yes	no	no	no
Industry-municipality FE	yes	yes	yes	yes
Municipality-year FE	no	yes	yes	yes
Firm FE	no	no	yes	yes
Observations	1,168,496	1,168,496	1,168,496	1,168,496

Notes: All regressions are run at the firm-level through OLS. *HHI* are computed at the 4-digit industry- municipality level. Regressions (1) through (3) are unweighted, while regression (4) is weighted by firm-level employment. Standard errors (in parentheses) are clustered at the 4-digit industry-municipality level. Key: \*\*\* significant at 1 percent; \*\* 5 percent; \* 10 percent.

We now discuss results for our variable of interest: labor market concentration. In addition to log labor productivity, Column 1 includes year and industry-municipality fixed effects as controls, exploiting variation in labor concentration within labor markets. Next, column 2 includes a more flexible specification for the year effects, interacting them with municipality fixed effects to control for local-level demand and supply shocks common to all industries. Finally, columns 3 and 4 present our preferred specifications, where we include firm fixed effects to control for differences in average labor composition across firms. Thus, these estimates are based on variation in labor concentration within a given firm and labor market.

Results in Table 2 underline the importance of controlling for idiosyncratic firm differences. In columns 1 and 2, we find a positive and statistically significant coefficient on labor market concentration, suggesting that wages are higher in more concentrated labor markets<sup>13</sup>. However, when we include firm fixed effects in columns 3 and 4, these coefficients turn negative. These results suggest that, while firms located in more concentrated labor markets hire a more significant proportion of high-wage workers, they tend to pay them lower wages when labor market concentration increases. Interestingly, coefficients in unweighted (column 3) and labor-weighted (column 4) regressions are quite similar—around -0.045. This suggests that average wages are impacted similarly by employment concentration in small and large firms. The estimated coefficient implies a moderate effect of labor concentration: increasing labor concentration by one standard deviation (0.324) decreases wages by 1.5 percent<sup>14</sup>.

### 5.3.2. Instrumental Variable Results

As we discuss in section 4.2, variation in the *HHI* does not arise exogenously, but may be driven by the same factors that move average wages. Table 3 presents 2SLS results, where we use the one-leave-out *HHI* described in section 4.2 as an instrument for the employment *HHI*. Panel A reports reduced form regressions, where we directly regress log average wages on the instrument. Across specifications, we find a strong negative relationship between the two variables, providing support to the relevance of the instrument.

Next, panel B reports the first stage results, where we instrument *HHI* by the leave-one-out *HHI* instrument. The first stage works well, with an F-statistic substantially above the Stock-Yogo critical value of 16.4 for 10 percent maximal IV bias. The coefficient on the instrument is positive and highly significant with a magnitude that varies little across specifications. This implies that labor market concentration in a particular industry-municipality is positively correlated with the labor market concentration of the same industry in the rest of municipalities of the country. The magnitude of the first-stage coefficient implies that a ten percent increase in the *HHI* of other municipalities is associated with an increase in *HHI* that varies between 1.1 percent and 1.8 percent.

Finally, panel C shows the second-stage results. The estimated coefficient on labor market concentration is negative and highly significant in all specifications. This suggests that firms in more concentrated markets tend to pay lower average wages. The coefficient is notably larger than the OLS coefficient in panel A, indicating that without instrumenting for the endogenous *HHI*, results are biased towards zero. In quantitative terms, we find a plausible response of trade credit to changes in markups: based on the IV coefficient in column 3, a typical change in employment concentration within an industry-municipality pair (0.036) reduces average wages by 2.2 percent ( $0.036 \times 0.679 = 0.220$ ). As in the case of OLS regressions, weighting observations by firm employment does little to impact coefficients, suggesting a similar response across firm sizes.

<sup>13</sup> Rinz (2020) reports a positive relationship between average wages and employment concentration in OLS regressions for the United States. Similarly, Autor et al. (2020) find a positive relationship between wages and product market concentration in the U.S.

<sup>14</sup> For comparability with other studies, the estimated coefficient in column 3 implies an average wage-*HHI* elasticity of 3.2 percent.



**Table 3.** Labor Market Concentration and Wages: 2SLS Results

	(1)	(2)	(3)	(4)
<b>A. Reduced Form</b>				
Dependent variable:	$\log \bar{y}_{mjt}$	$\log \bar{y}_{mjt}$	$\log \bar{y}_{mjt}$	$\log \bar{y}_{mjt}$
H-HI	-.0905*** (.0161)	-.0911*** (.0156)	-.120*** (.0140)	-.0771** (.0311)
log(labor productivity)	.231*** (.00296)	.231*** (.00297)	.0830*** (.00154)	.864*** (.00409)
<b>B. First stage</b>				
Dependent variable:	<i>HHI</i>	<i>HHI</i>	<i>HHI</i>	<i>HHI</i>
H-HI	.170*** (.0144)	.183*** (.0135)	.141*** (.0135)	.113*** (.0203)
log(labor productivity)	.00196*** (.000145)	.00152*** (.000127)	.00108*** (.000202)	-.0030*** (.00089)
First-stage F-statistic	350.3	438.5	245.9	77.3
<b>C. Second stage</b>				
Dependent variable:	log(y)	log(y)	log(y)	log(y)
H HI	-.531*** (.105)	-.497*** (.0917)	-.854*** (.125)	-.679** (.308)
log(labor productivity)	.232*** (.00296)	.232*** (.00296)	.0839*** (.00154)	.0843*** (.00408)
Weighted	no	no	no	Employment
Year FE	yes	no	no	no
Industry-municipality FE	yes	yes	yes	yes
Municipality-year FE	no	yes	yes	yes
Firm FE	no	no	yes	yes
Observations	1,168,496	1,168,496	1,168,496	1,168,496

Notes: All regressions are run at the firm-level. *HHI* are computed at the 4-digit industry-municipality level. Panel A reports reduced form specifications, where we directly regress log average wages against the instrument. Panel B reports the first stage results of IV regressions reported in panel C, together with the (cluster-robust) Kleibergen-Paap rKWald F-statistic. The corresponding Stock-Yogo value for 10 percent maximal IV bias is 16.4. Second stage results are reported in panel C. Standard errors (in parentheses) are clustered at the 4-digit industry-municipality level. Key: \*\*\* significant at 1 percent; \*\* 5 percent; \* 10 percent.

### 5.3.3. Within-Firm Distributional Effects

Next, we further investigate how labor market concentration affects different percentiles of the within-firm wage distribution. For this, we re-estimate equation (6) using different percentiles of firm wages instead of the average value of wages within firms. Table 4 shows the results, focusing on our preferred specification with market, municipality-year and firm fixed effects. We only show second-stage results, as the first-stage is the same as in column 3 of Table 3.

**Table 4.** Labor Market Concentration and Within-Firm Wage Distribution

Percentiles wage distribution:	P10 (1)	P25 (2)	P50 (3)	P75 (4)	P90 (5)
<i>HHI</i>	-.256 (.191)	-.748*** (.169)	-.995*** (.151)	-.863*** (.132)	-1.047*** (.145)
log(labor productivity)	.259*** (.00261)	.191*** (.00216)	.113*** (.00178)	.0609*** (.00166)	.0239*** (.00173)
First-stage F-statistic	245.9	245.9	245.9	245.9	245.9
Industry-municipality FE	yes	yes	yes	yes	yes
Municipality-year FE	yes	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes	yes
Observations	1,168,496	1,168,496	1,168,496	1,168,496	1,168,496

Notes: All regressions are run at the firm-level and instrument observed (4-digit) industry-municipality *HHI* with the average (employment-weighted) *HHI* across other municipalities where the industry operates. The table reports for all regressions the (cluster-robust) Kleibergen-Paap rKWald F-statistic. The corresponding Stock-Yogo value for 10 percent maximal IV bias is 16.4. Standard errors (in parentheses) are clustered at the 4-digit industry-municipality level. Key: \*\*\* significant at 1 percent; \*\* 5 percent; \* 10 percent.

Two results stand out. First, labor productivity correlates more strongly with wages at the bottom of firms' wage distribution than with wages at the top. This suggests that firms' top wages are likely determined by factors other than average labor productivity. This could occur, for instance, if managers pay relatively high wages to attract specific skills, or if high-wage workers have relatively greater bargaining power when setting wages than low wage workers do.

Turning to our variable of interest, we observe that labor market concentration affects workers differently depending on their position within the wage distribution. Column 1 shows that the negative effect of labor market concentration is non-significant for workers in the tenth percentile of the wage distribution. The point estimate (-0.256) is only 30 percent of the average value estimated in Table 3. However, as we move upwards in the wage distribution, we observe that the negative effect of labor concentration increases (in absolute value). In quantitative terms, the coefficient changes more significantly when moving from percentile 10 to 25 (column 1 to 2). In this case, the coefficient almost triples, jumping from -0.256 to -0.748. Moving further up the distribution somewhat increases the coefficient on labor concentration, although non-monotonously. Results on columns 3 to 5 show that the *HHI* coefficient ranges between -0.86 and 1.05 for the 50<sup>th</sup>, 75<sup>th</sup>, and 90<sup>th</sup> percentiles. As a consequence, within-firm earnings dispersion falls with labor market concentration (Table 5)<sup>15</sup>.

<sup>15</sup> A word of caution is due. The data only consider formal employment. Thus, it may be possible that differences across worker types reflect the presence of informal work. Alternatively, it may be the case that the wage of low-wage formal workers is less sensitive to differences in labor market power because, for these workers, the possibility of transitioning to informal employment is an outside option that high-wage workers do not have.

**Table 5.** Labor Market Concentration and Wage Dispersion

Dispersion variable:	log(P90/P10) (1)	log(P50/P10) (2)	log(P90/P50) (3)	SD(wages) (4)
<i>HHI</i>	-.791*** (.202)	-.739*** (.168)	-.0515 (.0999)	-5.106*** (.967)
log(labor productivity)	-.236*** (.00265)	-.146*** (.00176)	-.0892*** (.00140)	-1.211*** (.0156)
First-stage F-statistic	245.9	245.9	245.9	245.9
Industry-municipality FE	yes	yes	yes	yes
Municipality-year FE	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes
Observations	1,168,496	1,168,496	1,168,496	1,168,496

Notes: All regressions are run at the firm-level and instrument observed (4-digit) industry-municipality *HHI* with the average (employment-weighted) *HHI* across other municipalities where the industry operates. The table reports for all regressions the (cluster-robust) Kleibergen-Paap rKWald F-statistic. The corresponding Stock-Yogo value for 10 percent maximal IV bias is 16.4. Standard errors (in parentheses) are clustered at the 4-digit industry-municipality level. Key: \*\*\* significant at 1 percent; \*\* 5 percent; \* 10 percent.

To sum up, we find two main results. First, we document a strong negative relationship between labor market concentration and average wages. This confirms hypothesis 1. However, we reject Hypotheses 2, as we find robust evidence that labor concentration affects workers differently depending on their position within the wage distribution. Perhaps surprisingly, we find that low-wage workers are relatively less affected by employment concentration than high-wage workers. As we discuss in section 2, this may be due to a more elastic labor supply of these workers, who have more general skills and can move more easily across industries in a given location. Besides, low-wage workers' salaries are closer to the minimum wage threshold set by the Chilean authorities. Regardless of the specific mechanism, the relatively larger drop in the salary of high-wage workers with employment concentration leads to a compression of the within-firm wage dispersion.

### 5.1. Interaction with Product Market Power

Table 6 shows the results of the interactions between labor market concentration and markups. We focus the discussion on our preferred specification for all outcomes, where we include market, municipality-year, and firm fixed effects, and instrument both the *HHI* and markups by the instruments presented in section 4. Column 1 shows results using log average wages as the dependent variable, while columns 2 through 6 regress different percentiles of the within-firm wage distribution as outcomes.

A word of caution is due before discussing the coefficients in Table 6. The first-stage regression, where we instrument *HHI*, markups and their interaction with the instruments presented in section 4, delivers a moderate value of 13.8 for the F-statistic. While this value is above the Staiger and Stock (1997) "rule-of-thumb" value of 10, it is considerably lower than our baseline estimates in Table 3. For this reason, our 2SLS results for the interaction between the *HHI* and markups should be interpreted as an exploratory analysis.

**Table 6.** Labor Concentration and Wages: Heterogeneity with Firm Markups

Dependent variable:	(1) Average	(2) P10	(3) P25	(4) P50	(5) P75	(6) P90
<i>HHI</i>	-1.180*** (.270)	-.341 (.375)	-1.055*** (.338)	-1.233*** (.289)	-1.232*** (.277)	-1.439*** (.311)
ln(Markup)	-1.267*** (.263)	-1.384*** (.340)	-1.483*** (.326)	-1.381*** (.282)	-1.184*** (.275)	-1.273*** (.306)
<i>HHI</i> × ln(Markup)	1.464*** (.494)	1.103 (.737)	1.562** (.635)	1.285** (.517)	1.509*** (.508)	1.589*** (.561)
log(labor productivity)	.0115 (.0231)	.168*** (.0303)	.103*** (.0285)	.0258 (.0246)	-.00331 (.0242)	-.0455* (.0272)
First-Stage F-statistic	13.8	13.8	13.8	13.8	13.8	13.8
Industry-municipality FE	yes	yes	yes	yes	yes	yes
Municipality-year FE	yes	yes	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes	yes	yes
Observations	1,101,451	1,101,451	1,101,451	1,101,451	1,101,451	1,101,451

Notes: All regressions are run at the firm-level and instrument observed (4-digit) industry-municipality *HHI* with the average (employment-weighted) *HHI* across other municipalities where the industry operates. The table reports for all regressions the (cluster-robust) Kleibergen-Paap rKWald F-statistic. Standard errors (in parentheses) are clustered at the 4-digit industry-municipality level. Key: \*\*\* significant at 1 percent; \*\* 5 percent; \* 10 percent.

We begin by discussing the conditional relation between wages and markups. As for the case of labor market concentration, we find that firm-level markups are negatively related to workers' wages, suggesting that high-markup firms pay lower wages on average. Interestingly, markups operate in addition to the effect of labor market concentration; for all regressions, we find that the labor market concentration coefficient varies little when controlling for firm-level markups. The coefficient on average markups (column 1) is -1.27, which is about the same order of magnitude as the effect of the *HHI*. However, unlike the *HHI*, markups have a similar effect on workers' earnings in different percentiles of the wage distribution. There seems to be a stronger negative effect on the earnings of low-wage workers, if any. These differences are not quantitatively meaningful; the markup coefficient is about -1.400 for the 10<sup>th</sup> through 25<sup>th</sup> percentiles, -1.381 for the 50<sup>th</sup> percentile and about -1.250 for the 75<sup>th</sup> through 90<sup>th</sup> percentiles.

We now turn to discuss the estimated interaction term between employment concentration and firm-level markups. Across specifications, we find a positive interaction term coefficient that lessens—but does not overturn—the negative effect of labor market concentration on average wages<sup>16</sup>. Thus, while high-markup firms exploit their advantageous hiring position in concentrated labor markets by paying lower wages, the resulting wage markdown is more moderate than the wage markdown charged by other, low-markup firms. To shed light on the mechanism, column 2 through 6 explores how the average relationship varies across different percentiles of the within-firm wage distribution. While the interaction term between the *HHI* and markups is non-significant for workers earning wages at the bottom of the within-firm wage distribution, the interaction term coefficient turns highly significant as we move up the wage distribution. This suggests that high-markup firms share a higher proportion of their

<sup>16</sup> The only exception occurs when using the tenth wage percentile as the outcome variable. In this case, the point estimate for the *HHI* turns positive for firms with markups above 1.28. Nevertheless, this effect is non-significant.

rents with workers, either hiring “better,” high-wage workers or giving up a part of the rents to retain high-wage workers.

Finally, Table 7 shows results for within-firm wage dispersion, focusing on the (log) percentiles, 90-10 ratio and the standard deviation of firm wages. Confirming results in Table 5, we find that labor market concentration reduces within-firm wage dispersion. However, unlike wage levels, wage dispersion is only weakly related to markups. The coefficient of markups is non-significant, and the coefficient on the interaction term between the *HHI* and markups is positive, but only significant at the 10 percent level when the standard deviation of firm wages is used as the dependent variable.

**Table 7.** Labor Concentration and Wage Dispersion: Heterogeneity with Firm Markups

Dependent variable:	(1) (P90/P10)	(2) St.dev.
<i>HHI</i>	-1.098*** (.380)	-7.126*** (1.804)
ln(Markup)	.111 (.346)	-1.546 (1.665)
<i>HHI</i> × ln(Markup)	.487 (.711)	5.441* (3.220)
log(labor productivity)	-.213*** (.0317)	-1.185*** (.151)
First-Stage F-statistic	13.8	13.8
Industry-municipality FE	yes	yes
Municipality-year FE	yes	yes
Firm FE	yes	yes
Observations	1,101,451	1,101,451

Notes: All regressions are run at the firm-level and instrument observed (4-digit) industry-municipality *HHI* with the average (employment-weighted) *HHI* across other municipalities where the industry operates. The table reports for all regressions the (cluster-robust) Kleibergen-Paap rKwald F-statistic. Standard errors (in parentheses) are clustered at the 4-digit industry-municipality level. Key: \*\*\* significant at 1 percent; \*\* 5 percent; \* 10 percent.

## 6. Conclusions

Economic concentration has significant effects on individuals’ welfare. This paper uses a rich employer-employee dataset to study the impact of labor market concentration on workers’ earnings in Chile. We find a robust negative relationship between concentration and average wages. This relationship is heterogeneous: high-wage workers’ earnings are impacted more negatively than low-wage workers’ earnings, ultimately leading to a negative relationship between within-firm earnings dispersion and concentration.

We show that average worker earnings in high-markup firms decrease less with employment concentration. To explain this finding, we hypothesize two non-competing mechanisms. First, high-markup firms may be sharing a higher proportion of their rents to retain “better,” high-wage, workers. Second, high market power firms may be using their advantageous hiring position to “upskill” their labor force. Macaluso et al. (2019) provide supporting evidence for this last mechanism, using granular data on vacancies in the United States. We note that these mechanisms are non-exclusive, and that the reduced form relationship may reflect a combination of both mechanisms.

The results on employment concentration and price-cost markup have two implications. First, they suggest that in more concentrated labor markets, workers employed by high-market power firms are better off than workers employed by low-market power firms. Second, it implies that product market power may explain part of the observed between-firm wage dispersion.

Our results shed light on the effect of economic concentration in developing economies. As such, we underline the need for more research to understand whether the patterns observed in the Chilean labor markets hold more generally in other emerging economies. We believe our results pave the road for several avenues of future research. First, which mechanism—rent-sharing or upskilling of the labor force—accounts for the more moderate effect of employment concentration in high-markup firms? Second, does the improvement in the quality of the labor force in high-markup firms provide them an advantage to increase their market power further in the future?

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## Appendix. Labor Market Concentration and Earnings: Evidence from Chile

### A. Estimating Markups

Following recent developments in industrial organization (e.g., De Loecker et al., 2020), we argue that market power—the ability of firms to charge prices above their marginal cost—can be well approximated by firm-level markups. Importantly, the markup between price and marginal costs may reflect factors other than market power, such as the existence of significant overhead or fixed production costs. We address this concern by defining the measures in relative terms, comparing each plant’s markup to the median markup in the industry. Under the assumption that differences in overhead and fixed costs are purely technological, such a comparison would, in part, address the concern mentioned above. Also, as De Loecker et al. (2020) show, markups are highly correlated with different measures of profitability, including accounting profits and stock market performance. Thus, we believe that markups are a good approximation of market power.

We follow De Loecker and Warzynski (2012) to recover plant-level markups from the plant’s optimality conditions under the assumption that (i) at least one input ( $V$ ) is fully flexible, and (ii) plants minimize costs for each product  $j$ . The plant’s first-order condition of its cost minimization problem for the flexible input  $V$  can be rearranged to obtain the markup of plant  $i$  at time  $t$  as:

$$\underbrace{\mu_{it}}_{\text{Markup}} \equiv \frac{P_{it}}{MC_{it}} = \underbrace{\left( \frac{\partial Q_{it}(\cdot)}{\partial v_{it}} \frac{v_{it}}{Q_{it}} \right)}_{\text{Output Elasticity}} \bigg/ \underbrace{\left( \frac{P_{it}^V \cdot v_{it}}{P_{it} \cdot Q_{it}} \right)}_{\text{Expenditure Share}}, \quad (1)$$

where  $P$  ( $P^V$ ) denotes the price of output  $Q$  (input  $V$ ) and  $MC$  is marginal cost. This implies that the markup can be computed by dividing the output elasticity for the flexible input by its expenditure share (relative to the sales of product  $j$ ). While the numerator of equation (1)—the input-output elasticity—needs to be estimated, the denominator is directly observable in our data. We next explain the procedure for deriving each of these elements.

#### 6.1.1. Input-output elasticity

To estimate the input-output elasticities, we specify production functions using labor ( $L$ ), capital ( $K$ ) and materials ( $M$ ) as production inputs:

$$Q_{it} = \Omega_{it} K_{it}^{\alpha_K} L_{it}^{\alpha_L} M_{it}^{\alpha_M} \exp(\varepsilon_{it}) \quad (2)$$

where  $Q$  is output, and  $\Omega$  denotes firm productivity. Our baseline specification assumes a Cobb-Douglas production function and allows for the presence of a log-additive non-anticipated shock ( $\epsilon$ )<sup>17</sup>.

Physical output  $Q_{it}$  is not observed in the data. Thus, we follow De Loecker (2011), and proxy for the unobserved price component by introducing a standard horizontal differentiation demand system with constant elasticity of substitution (CES) for each industrial sector  $s$ :

$$Q_{it} = Q_{st} \left( \frac{P_{it}}{P_{st}} \right)^{\eta_s} \quad (3)$$

The demand faced by each firm  $i$  depends of its own price ( $P_{it}$ ), the aggregate price in the industry ( $P_{st}$ ) and an aggregate demand shifter ( $Q_{st}$ )<sup>18</sup>. As Klette and Griliches (1996) and Levinsohn and Melitz (2006) show, the demand (3) can be used to control for the price component  $P_{it}$  in the estimation of the production function (2) in absence of physical output information. Replacing (3) in (2) yields:

$$R_{it} = P_{it} \cdot Q_{it} = Q_{it}^{\frac{\eta_s+1}{\eta_s}} Q_{st}^{-\frac{1}{\eta_s}} P_{st} \quad (4)$$

After deflating nominal revenues with sector-specific price deflator ( $R_{it}^* \equiv R_{it}/P_{st}$ ), the production function's estimating equation is (where lowercases denote logarithms of the variables):

$$\tilde{r}_{it} = \beta_L l_{it} + \beta_K k_{it} + \beta_M m_{it} + \beta_s q_{st} + \omega_{it}^* + \epsilon_{it} \quad (5)$$

As pointed out by De Loecker (2011), the production function coefficients in (5) combine production and demand parameters:  $\beta_h \equiv \alpha_h \cdot (\eta_s + 1)/\eta_s$  for  $h = \{L, K, M\}$ , and  $\beta_s = 1/\eta_s$ . Similarly, measured productivity  $\omega^*$  is a scaled version of real productivity:  $\omega^* \equiv \omega(\eta_s + 1)/\eta_s$ .

The estimation of (5) follows Akerberg et al. (2015) (henceforth, ACF), who extend the methodology proposed by Olley and Pakes (1996) and Levinsohn and Petrin (2003) to control for the endogeneity of firms' inputs choice, which is based on the actual level of firms' productivity<sup>19</sup>. To identify the coefficients of the production function, we build moments based on the productivity innovation  $\zeta$ , under the standard assumption that productivity follows a

<sup>17</sup> A shortcoming of the Cobb-Douglas specification is that it assumes that input-output elasticities are constant across firms and over time. On the other hand, the Cobb-Douglas specification is widely used, allowing for a more direct comparison of our results with other estimates in the literature.

<sup>18</sup> This demand system implies that it is optimal for the firm to charge a price equal to a constant markup ( $\eta_s/(\eta_s + 1)$ ) over its marginal cost. The demand can be modified to include unanticipated demand shocks as in De Loecker (2011). However, we do not specify these shocks because our data do not allow us to identify them as in De Loecker (2011).

<sup>19</sup> ACFs show that the labor elasticity is in most cases unidentified by the two-stage method of Olley and Pakes (1996) and Levinsohn and Petrin (2003).

first-order Markov process. In addition, we follow Olley and Pakes (1996) in including the probability of remaining active to correct for the bias that results from non-random firm exit.

The first step of the ACF procedure involves expressing productivity in terms of observables. To do so, we use inverse material demand  $h_t(\cdot)$  as in Levinsohn and Petrin (2003) to proxy for unobserved productivity, and estimate expected output  $\varphi_y(k_{it}, l_{it}, m_{it}; x_{it})$  to remove the unanticipated shock component  $\varepsilon_{it}$  from (5)<sup>20</sup>. Then, the ACF procedure exploits this representation to express productivity as a function of data and parameters  $\omega_{it}(\alpha) = \hat{\varphi}_t(\cdot) - \alpha_k k_{it} - \alpha_l l_{it} - \alpha_m m_{it}$ , and form the productivity innovation  $\zeta_{it}$  as a function of the parameters  $\alpha$ . The second step of the ACF routine forms moment conditions on  $\zeta_{it}$  to identify all parameters  $\alpha$  through GMM:

$$\mathbb{E}(\zeta_{it}(\alpha) \cdot Z_{it}) = 0 \quad (6)$$

where  $Z_{it}$  contains lagged materials, labor, capital and current capital. Once the parameters are estimated, the input-output elasticities are recovered for each product as  $\theta_{it}^V \equiv \partial \ln Q_{it} / \partial \ln V_{it}$ . For the Cobb-Douglas case,  $\theta_{it}^V = \alpha_v$ , so that the input-output elasticity is constant for all firms.

### 6.1.2. Implementation

To derive markups, we use materials as the relevant flexible input to compute the output elasticity. While in principle, labor could also be used to compute markups, the existence of long-term contracts and firing costs make firms less likely to adjust labor after the occurrence of shocks (see Montenegro & Pagés, 2004). The second component needed in (1) to compute markups is the expenditure share, which we calculate by dividing the value of material inputs by revenues, both observed in the data.

## B. Aggregate Trends

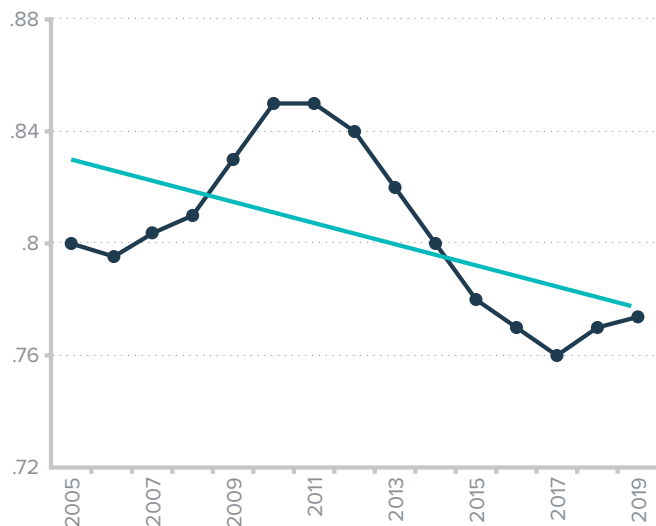
### 6.1. Earnings Dispersion

Figure B.1 plots the variance of log earnings over the period 2005-2019. The evolution of overall earnings dispersion can be separated into two periods, each spanning about four to five years. From 2005 to 2010, there was a significant rise in earnings dispersion, with the variance of total earnings increasing 0.047 log points. After 2010, total earnings variance shows a steady decline until 2017, falling almost 0.10 log points from its peak in 2010<sup>21</sup>.

<sup>16</sup> The vector  $x_{it}$  includes other variables that affect material demand, such as time and product dummies. We approximate  $\varphi_t(\cdot)$  with a full second-degree polynomial in capital, labor and materials.

<sup>21</sup> When compared with the evolution of aggregate income inequality, earnings dispersion shows a more nuanced picture. When using household-level surveys, the aggregate data show a mild steady decline in income inequality from 2005 to 2017.

**Figure B.1.** Variance of Log Annual Earnings in Chile, 2005-2019



Notes: The figures show binscatter diagrams where the average trade credit share in each bin is plotted against markups (panel A), and relationship length (panel B). Markups are computed at the firm- product level as in De Loecker et al. (2016). Relationship length is measured in terms of the number of transactions in each destination and product. Markups and relationship length are expressed in terms of logarithms. Both figures control for destination-year fixed effects.

To understand the role of firms in explaining the evolution of earning dispersion, we follow Song et al. (2019) and Alvarez et al. (2018) and decompose the variance of total earnings in its within-firm and between-firm components. Let  $y_{ijt}$  denote the logarithm of earnings of worker  $i$  employed by firm  $j$  in period  $t$ . Then the following identity should hold by definition:

$$y_{ijt} = \bar{y}_{jt} + [y_{ijt} - \bar{y}_{jt}] \quad (7)$$

where  $\bar{y}_{jt}$  denotes the average earning of firm  $j$  in period  $t$ . Equation (7) is useful because it allows decomposing the total variance of log earnings in between-firm and within-firm variances<sup>22</sup>.

$$Var(y_{ijt}) = Var(\bar{y}_{jt}) + \sum_j \omega_j \times Var(\bar{y}_{ijt} | i \in j) \quad (8)$$

where  $\omega_j$  denotes the employment share of firm  $j$ . The first term on the right-hand side of equation (8) represents the variance of the average firm-level log earnings (weighted by the number of workers in each firm). In contrast, the second term shows the (employment-weighted) average of within-firm dispersion in log earnings.

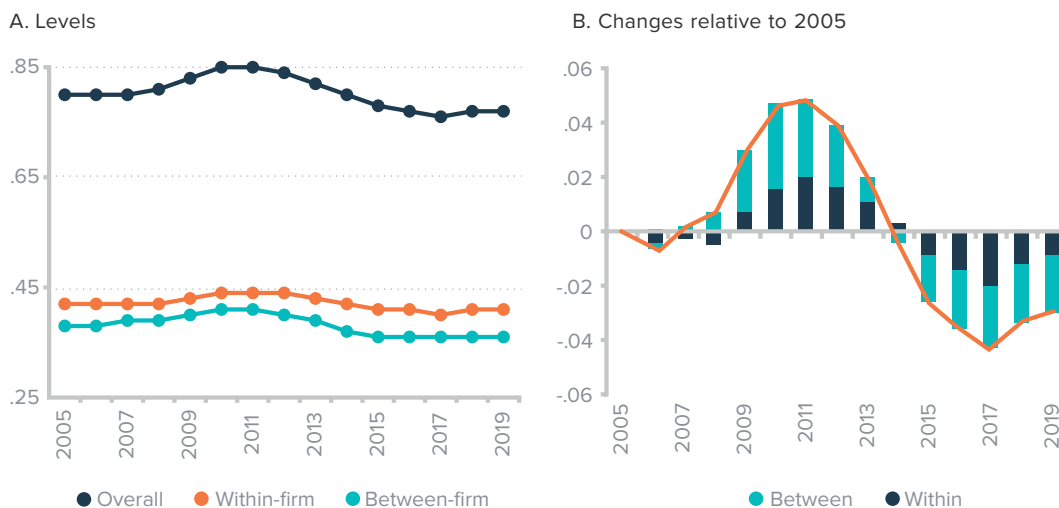
<sup>22</sup> In particular, to arrive to the expression for within-firm variance it is necessary to use the law of iterated variance.

Figure B.2 plots the evolution of within-firm and between-firm variance for Chile. We note that both components contribute approximately similar proportions to the level of earnings dispersion (panel A). Nevertheless, when assessing changes in the dispersion of total earnings, we find that between-firm variance contributed about two-thirds of the observed change in total earnings dispersion, while within-firm variance contributed only one-third (panel B). In quantitative terms, between-firm variance accounted for 0.031 of the 0.047 log points increase in total variance between 2005 and 2010, and for 0.053 of the 0.076 log points decrease in total variance observed between 2009 and 2019.

We summarize the results of this subsection as follows:

**Result 1.** Earnings dispersion in Chile shows a slightly negative trend since 2005. This trend is mostly accounted for by a significant drop in earnings dispersion between 2010-2016, when earnings variance fell 0.09 log points. Finally, between-firm variance accounts for about two-thirds of the change in total earnings variance.

**Figure B.2.** Decomposition of the Variance of Log Annual Earnings: Within and Between Components



Notes: The figures show the evolution of the concentration ratio for the third- and fifth-largest firms in each industry. We compute the index for each 3-digit ISIC industry (revision 4), and then aggregate as weighted (panel A, using sales shares) and unweighted averages (panel B).

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