Labor-Market Concentration and Workers Outcomes: Evidence from Chile*

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Abstract

This paper studies the effect of local labor market concentration on earnings in Chile from 2005 to 2019. Unlike most of the previous literature – that sets local labor markets based on administrative boundaries – we endogenously define them using the information on job-to-job transitions across different localities. Our results show that earnings are lower in more concentrated labor markets, particularly in larger firms. We find that concentration compresses the within-firm earnings distribution by having a more substantial adverse effect on workers' earnings at the upper end of the distribution. This result does not seem to be driven by changes in composition. The negative effects of concentration appear to be stronger for high-skilled workers.

JEL: J31, J42, J61

Keywords: Monopsony power, job mobility, labor market concentration, market power, Chile

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1 Introduction

A large body of literature has documented growing levels of concentration in input and output markets over the last two decades (Autor et al., 2020; De Loecker and Eeckhout, 2018). Most of the attention has focused on the causes and consequences of output markets' concentration and how it can affect consumers' welfare. Comparatively, less attention has been given to the effects of concentration in input markets, particularly labor, despite its potentially large implications for the welfare of workers or the allocation of employment across sectors and firms.

In fact, market concentration on both ends is likely to have a relevant impact on the labor market. Ceteris paribus, market power in output, which reduces the production of final goods relative to its optimal level, will dampen the demand for labor, reducing employment and equilibrium wages. Similarly, market power from firms hiring labor will push wages below their competitive equilibrium, away from the marginal product of labor that would prevail in perfect competition. While at first glance these patterns are conceptually clear and have found empirical support in the U.S. and Europe (see Azar et al., 2020; Benmelech et al., 2020; Rinz, 2020, among others for U.S. based evidence), there is less empirical evidence for developing countries. Additionally, there is relatively scant evidence of how these effects vary across different types of firms and workers. For example, as long as market concentration has a heterogeneous impact on workers with different skills, changes in market concentration could be related to variations in earnings inequality.

Additionally, most of the evidence has come from average wages at the firm level. In that context, the connection to the wages of individual workers is not obvious, as market concentration could also affect the composition of firms among workers of different skills. Moreover, on a dynamic setup, concentration could also affect earnings dynamics through its effects on the returns to tenure and job transitions.

This paper contributes to this debate by studying the relationship between labor market concentration and wages using a rich administrative employer-employee dataset for Chile that contains information for the universe of formal firms and workers. We use the dataset to construct highly disaggregated local labor concentration measures, in line with evidence that shows that the bulk of workers seek jobs locally (Manning and Petrongolo, 2017; Marinescu and Rathelot, 2018). This implies that the extent of a local labor market can be conceptually understood as a geographical area where most job transitions occur, such that worker movements outside the area are comparatively rarer. In that sense, a local labor market captures the bulk of the relevant job opportunities available to workers. Accordingly, we exploit employment concentration differences across narrowly defined industries and geographic areas to identify the relationship between concentration and wages.

Besides being interested in the relationship between concentration and average firm wages, as in much of the previous literature, we also want to disentangle the forces underlying those results and how effects can vary across different groups of workers. Therefore, we study how average effects relate to changes in the within-firm wage distribution and the composition of workers employed in the firms. Moreover, we look at whether average effects hide a heterogeneous impact across workers with different skills that are likely to face different outside options. For example, high-skill workers might have higher bargaining power with the firm as they might be harder to substitute, which could buffer their wages from the effects of concentration. However, they may have more firm-specific human capital that might limit their mobility. On the other hand, low-skill workers might be easier to replace but also more capable of finding a new job easily and are protected by the minimum wage restrictions. Therefore, while the net effects are unclear *ex-ante*, it seems likely that the effects of concentration on earnings vary across worker types. We expect to exploit these differences further in future work as we study how effects vary across incumbent workers vs. new hires and how labor market power relates to job transition and longer-term earnings dynamics.

Unlike most of the previous literature, our definition of local markets does not directly follow from administrative divisions, which in the case of Chile, go, from the most to the least aggregate, from regions to provinces to municipalities. As mentioned earlier, from a geographical perspective, local markets can be understood as the extent of the area where the worker is most likely to move to a new job. In that context, small administrative divisions, such as municipalities, might be too narrow, as workers can easily move across those borders, especially in urban areas, where several municipalities exist within a city. Larger administrative divisions, such as regions or provinces, on the other hand, might be too broad. Therefore, we take advantage of the data and define local markets by looking at the intensity of job transitions across municipalities, following the Hierarchical agglomerative clustering (HAC) method (Tolbert & Sizer, 1996).

To measure employment concentration, we focus on the widely used Herfindahl-Hirschmann Index (HHI). While the HHI is subject to criticisms – see Syverson (2019) for a discussion, we use it as our baseline measure of employment concentration to allow for direct comparability of our results with other studies. To address the potential endogeneity of the HHI, we follow Azar et al. (2020) and implement a 2SLS strategy using the average employment-weighted HHI in other local markets for the same industry and year as an instrument.

Our results show that more concentrated markets are associated with lower earnings. On our preferred specification with instrumental variables, a typical change in the HHI index is associated with a 4.5% reduction in average worker earnings. This is higher than the figure in Rinz (2020), who finds a one percentage point negative effect on wages in the US in a similar exercise. We also find that effects are more substantial in larger firms, as average effects grow almost three times when we weigh observations by the number of workers in the firm. This is consistent with the notion that larger firms exert more labor market power.

We also find that the average effects hinder a significant amount of heterogeneity. Indeed, the effect of employment concentration varies across workers' types, compressing the within-firm earnings distribution by having a more substantial adverse effect on workers' earnings at the upper end of the distribution. In quantitative terms, the effects of concentration in earnings are twice as large over the 75th percentile of the earnings distribution than over the 25th percentile. This finding is consistent with the notion that low-income workers are protected by minimum wage legislation or that their labor supply is relatively more elastic as they have a more general set of skills that allow them to find another job more easily, including the informal sector. Our results also suggest that changes in composition do not drive these effects on the earnings distribution: When we directly analyze the effects across worker skill types (as measured by individual worker fixed effects in earnings regressions), the adverse effects of concentration appear to be stronger for high-skilled workers. The estimated negative impact of concentration is twice as large for workers in the top skills quintile as it is for workers in the bottom two quintiles.

This paper is related to several strands of the literature. On the one hand, the growing literature on market power in input markets (Manning, 2011; Lamadon, Mogstad, and Setzler, 2022; Berger, Herkenhoff, and Mongey, 2022; among others) and its effect on worker earnings (Rinz, 2020; Azar et al, 2020; Felix, 2022; Marinescu et al, 2022). We contribute to that literature by providing novel evidence for a developing country and trying to disentangle the heterogeneous effects of concentration on different types of workers. Our interest in heterogeneity and the composition of firms also connects to the literature that addresses earnings inequality and its relationship to the characteristics of the workers and the structure of the labor market (Card et al, 2018; Sharma, 2022; Aldunate et al, 2020; Alvarez et al, 2018). Finally, we connect the literature on market power and earnings with the literature on the definition of local labor markets (Lucioletti, 2022; Adachi et al, 2021; Marinescu and Rothelot, 2018).

The remainder of the paper is organized as follows. 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 Data and Key Variables

2.1 Data sources

Our main source of data is a matched employer-employee census provided by the Chilean Internal Revenue Service (SII, by its Spanish acronym) between the years 2005 and 2019[1]. The dataset includes all firms that operate in the formal sector and all formal wage employment in Chile, which represents roughly 60% of the total employment in the country. Affidavit 1887, reported annually by each firm, records each employee's annual taxable earnings and her specific months of employment. Annual taxable earnings are the sum of all worker compensation forms, excluding social security payments. Therefore, the data can be used to calculate the total wage bill of each firm in a given year, as well as a measure of annual equivalent employment. Moreover, for each employment relationship, the data can be used to calculate the monthly average earnings of the worker in any given year.

SII assigns firms and workers in the administrative datasets unnamed and unique identifiers. This allows us to track individual labor histories across firms and time (with monthly frequency). We combine the information in Affidavit 1887 with firm-level information from form F22, the

[1] Affidavit N. 1887 of *Servicio de Impuestos Internos*.

main annual tax statement, and form F29, which provides monthly information on firms' sales and expenditures. This dataset provides on firms revenue and input expenditures, as well as information on the firm´s location (at the municipality level) and economic sector.

The tax dataset is also combined with information provided by the Chilean Register Office (*Servicio de Registro Civil e Identificación* in Spanish) to obtain the basic demographic characteristics (gender and date of birth) of each worker.

The main analysis only considers firms hiring at least two workers in a year to exclude self-employment. We follow additional steps to ensure a consistent dataset, including the deletion of (i) firms with missing geographical locations or industry and (ii) observations with zero or missing information for sales, material expenditure, or employment. The final database consists of 2,128,433 firm-year observations from 2005-2019.

2.2 Main variables

2.2.1 Local labor markets

Defining the scope of local labor markets is crucial for analyzing the effects of employment concentration. Implicit in the notion of local labor markets is the idea that, at least in the short term, they are segmented so that the relevant set of potential job positions for workers and candidates for firms are those in the labor market where they participate. While the existence of local labor markets is likely undisputed, a number of non-exclusive factors can lead to the emergence of segmented labor markets in equilibrium, including labor mobility costs or information frictions, among others.

The baseline analysis characterizes local labor markets as sector-location pairs each year. These dimensions intend to capture central features of typical workers' transitions across occupations but do not preclude the possibility that certain workers transition to jobs in different labor markets. By considering sectors, we aim to capture the extent to which workers' backgrounds help them to apply for jobs offered by other firms: The experience that a worker gains while working in furniture manufacturing, in general, is useless for applying to jobs in the pharmaceutical industry. Although this dimension is perhaps better captured by occupations, in the absence of detailed data on the task or occupations performed by workers within firms, we proxy for it by analyzing employment outcomes within economic sectors. In other words:

Within locations, our definition considers the relevant set of potential jobs where workers are competitive as those offered by firms operating in the same industry within a given location.

The second relevant dimension for defining local labor markets is geography. Ideally, local markets should be defined not by the boundaries of administrative divisions but by the observable behavior of workers and the implicit borders it defines in terms of their mobility. In that sense, the notion of local markets could be associated with the concept of commuting zones (Tolbert and Killian, 1987; Tolbert and Sizer, 1996), defining the extent of the area in which workers work and live. However, the computation of commuting zones requires detailed commuting information (origin-destination), which is not available in our data set.

While it seems natural to use administrative divisions to define local labor markets, they might fail to capture crucial elements defining labor markets, as they are designed to optimize the country's political administration rather than to represent the mobility patterns of workers. Indeed, in terms of administrative divisions, Chile is composed of 16 *regions*, 56 *provinces*, and 346 *municipalities*. Municipalities – the smallest administrative division – are too small, as typically, workers commute to neighboring municipalities to work and can easily change jobs to a nearby municipality without having to change their residence or drastically change their commute habits. This is particularly true in urban areas, where many municipalities are close and connected with multiple transportation options. In contrast, provinces and regions are too broad. While it is true that they encompass most of the workers' job transitions, they likely account for several local markets as workers move within specific areas within the region.

We approach the question of defining the relevant geographies underlying labor markets by applying the Hierarchical Agglomerative Clustering algorithm (Tolbert and Killian, 1987; Tolbert and Sizer, 1996) to job-to-job transitions across municipalities. This is, we look at the actual behavior of workers and how they change jobs to define the municipalities connected by a common set of relevant job opportunities and form a local market. Operationally, the algorithm requires defining a pair of localities, i and j, a stock of workers p, and a pair of flows of workers between i and j, (f_{ij}, f_{ji}). With this information, the algorithm computes a distance metric D_{ij} for each pair of municipalities i and j as follows:

$$D_{ij} \equiv \begin{cases} \max\left\{\varepsilon, 1 - \frac{f_{ij}, f_{ji}}{min(p_i, p_j)}\right\} & \text{for } i \neq j \\ 0 & \text{for } i = j \end{cases} \tag{1}$$

where ε is an arbitrarily small value, which we set to 0.001 as in Adachi et al. (2020). The algorithm iteratively merges municipalities with the lowest values of D_{ij}. In each step, the algorithm recomputes the matrix $\{D_{ij}\}$ considering the newly created geographical units. This procedure continues until all elements of the matrix $\{D_{ij}\}$ are above a predetermined threshold $\bar{D}$, which we set to 0.98, following Tolbert and Sizer (1996).

When applying the algorithm, we take a bottom-up approach to prevent obtaining discontinuing geographies. First, we restrict the set of potential merges to municipalities within regions. Then, after obtaining these new geographical units, we widen the search process to pairs of neighboring regions to allow the new geographical units to expand beyond the regional limits. We continue this process until eventually applying the algorithm at the national level. In every step, the procedure splits discontinuing units so that the area of all geographies is connected.

Figure 1 illustrate the resulting geographical units (which we refer to as "commuting zones") for the Santiago Metropolitan and Libertador Bernardo O'Higgins (LBO) regions. The left panel shows municipalities and provinces for these regions. As a reference, the northern six provinces in the Figure belong to Santiago metropolitan region, while the southern three to the LBO region. Then, the right panel illustrates the geographies delivered by the HAC algorithm. Interestingly, while the new geographies tend to have similar sizes and even overlap in some cases with provinces, they show stark differences. First, in some cases, the new geographies merge provinces, likely capturing conurbanizations such as the cases of the Santiago and Cordillera provinces, merged by the algorithm in a single unit. Second, the algorithm splits municipalities to create separate units, such as the Curacavi municipality located in the northwest area of Santiago Metropolitan. Finally, the Figure shows an example where the new geographical units include municipalities located in different regions: The southern part of the Melipilla region in Santiago Metropolitan, merged with Las Cabras municipality in the LBO region.

Figure 1. Illustration: HAC Commuting Zones for Metropolitan and Libertador Bernardo O'Higgins Regions

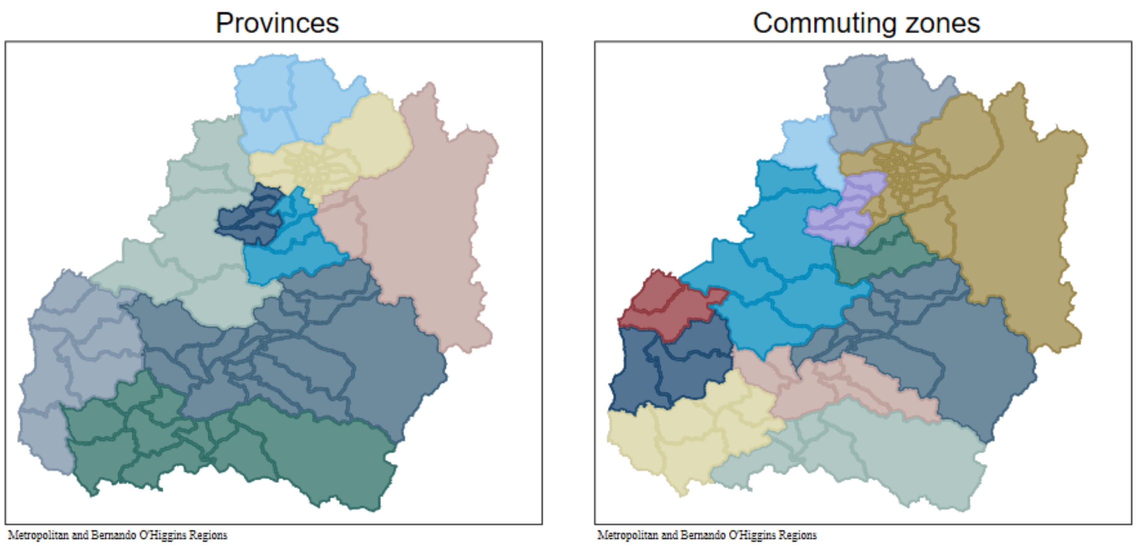


Table 1 compares the share of job-to-job transitions within different geographical units to characterize the resulting commuting zones further. The algorithm produces 56 commuting zones, almost the same number as provinces in Chile (55). As Figure 1 shows, while provinces and commuting zones tend to overlap, they generally consist of different aggregations of municipalities. Indeed, in only 7 cases, provinces and commuting zones are composed of the same municipalities. In only one-fourth of the job-to-job transitions, the source and destination firms locate in the same municipality. We note that this result remains even when excluding the Santiago Metropolitan region. In contrast, commuting zones capture over 63 percent of the overall transitions. This number is slightly larger than for provinces (61 percent), although the difference broadens when excluding the Santiago Metropolitan region. Finally, the fraction of job-to-job transitions that occur within regions is 0.7. Despite having the highest share, using regions as the relevant geographic area to define local labor markets may not be appropriate because regions are very large areas, and job change decisions within them may involve, for example, a change of residence.

Table 1. Employment Transitions within different market definitions

	Municipalities	**CZ**	**Province**	**Regions**
Job-to-Job Transitions (Share)				
All municipalities	0.253	0.629	0.607	0.698
(# geographical units)	(342)	(56)	(55)	(16)
Excluding cases provinces = CZ	0.251	0.637	0.615	0.700
(# geographical units)	(310)	(49)	(48)	(15)

2.2.2 Employment concentration

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 of this variable 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).[2] Formally, the employment-HHI for industry j operating in municipality m at year t is defined as

$$HHI_{mjt} \equiv \sum_{f=1}^{F} s_{fmjt}^2 \tag{2}$$

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

2.2.3 Earnings

While 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 percentiles 10, 25, 50, 75, and 90 of individual wages within firms and the standard deviation of individual earnings within firms. In all regressions, we control for labor

[2]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 of them – 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 3-digit ISIC level, as we believe this is a more conservative definition. Nevertheless, results are quantitatively similar when using the more disaggregated market definition.

productivity, computed as the ratio between value-added and the number of workers employed by the firm.

2.3 Summary Statistics

Table 2 shows descriptive statistics for the main firm characteristics and the baseline measure of labor concentration at the market-level. The data has information for 2,128,433 firm-year pairs over 2005-2019. The average firm reports sales for a value of 1.6 billion pesos (about 3.3 million U.S. dollars of 2013), employs 24 full time equivalent workers, pays an average monthly wage of 0.45 million pesos (about 920 U.S. dollars of 2013), and annual wage bill of 16.1 million pesos (about $ 32,800 U.S. dollars of 2013). All variables are positively skewed, with average values substantially above the respective median. For instance, the median firm reports 123 million pesos of sales ($251,000 U.S. dollars of 2013) and pays an annual wage bill of 1.42 million pesos ($ 2,900 U.S. dollars of 2013).

Table 2. Summary Statistics

	Mean	Std. Dev.	Percentiles 10	25	50	75	90	Observations
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Firm Characteristics								
Sales (CLP millions)	1,575	42,799	22	50	123	350	1,145	2,128,433
Employment (FTE)	24.4	189.6	1	2	4.5	11.8	32.7	2,128,433
Average wage (CLP millions)	0.45	0.51	0.19	0.23	0.30	0.49	0.82	2,128,433
Wage bill (CLP millions)	15.65	221.24	0.24	0.51	1.42	4.57	16.06	2,128,433
Average labor productivity (in logs)	16.1	1.2	14.8	15.5	16.2	16.8	17.5	2,128,433
Market Characteristics								
HHI (unweighted)	0.42	0.33	0.06	0.14	0.32	0.64	1.00	75,590
HHI (labor-weighted)	0.13	0.19	0.01	0.02	0.06	0.14	0.35	75,590
ΔHHI (unweighted)	-0.01	0.11	-0.09	-0.03	0.00	0.01	0.06	67,771
ΔHHI (labor-weighted)	-0.001	0.03	-0.02	-0.00	0.00	0.00	0.01	67,771
I(HHI=1)	0.14	0.35	0.00	0.00	0.00	0.00	1.00	75,590

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 from 2005-2019. The Herfindahl-Hirschmann Index (HHI) is computed using firms' employment shares over all firms in each 3-digit industry-commuting zone year. All nominal variables are expressed in millions of 2013 Chilean pesos.

Next, we discuss descriptive statistics for the baseline local labor market concentration measure. Across all markets and years, the unweighted average employment HHI is 0.42, with a standard deviation of 0.33 (80% of the average). From the 75,590 labor market-year observations, 14% of them are dominated by a single employee (HHI=1), but these highly concentrated markets tend to be relatively small. Indeed, when we weight markets by their aggregate employment, the average HHI falls to 0.13 with a standard deviation of 0.19.

3 Empirical Approach

This section presents the main empirical specifications we use to analyze the effect of employment concentration on worker outcomes. It also discusses threats to identification and introduces the instrumental variable approach we follow to address the endogeneity of the HHI.

3.1 Main Specification

The empirical analysis uses different outcome variables to study the effect of employment concentration on wages: (i) The average firm-level log wage, computed across all workers employed by the firm, (ii) Percentiles of the within-firm log earnings distribution, and (iii) Measures of within firm log wage dispersion. For each of these outcome variables y, we run the following specification:

$$y_{icjt} = \beta_1 \ln \mathrm{HHI}_{cjt} + \beta_2 X_{icjt} + \delta_{cj} + \delta_{ct} + \delta_i + \varepsilon_{icjt} \tag{3}$$

where i denotes a firm, c a commuting zone, j a 3-digit industry, and t denotes a year. HHI_{cjt} is the concentration index, which we compute at the commuting zone-industry-year level, and the vector X_{icjt} includes firm-level controls affecting firms' labor demand, such as the logarithm of labor productivity (i.e., value-added per employee). The baseline specification includes municipality-year fixed-effects, to control for local shocks, and commuting zone-industry fixed effects, to control for average differences across local labor markets. Our preferred specification includes firm fixed effects, which controls for average differences in the workforce composition across firms. All specifications clusters standard errors at the 3-digit industry-commuting zone level, corresponding to the level at which the HHI varies.

The coefficient of interest in regression (3) is β. We expect a negative value for β when using the average or different percentiles of the log wage distribution as dependent variables, that is, we expect lower wages in more concentrated labor markets.

In specification using measures of the log wage dispersion as dependent variables, different mechanisms are consistent with different values for β. For instance, if high-wage workers have a higher bargaining power when setting wages with employers than low-wage workers, we would expect an increase in log wage dispersion in more concentrated labor markets. But the opposite can also happen: Because the skills of low-wage workers tend to be more general, they can move more easily across industries. In such a case, low-wage workers would be less affected by employment concentration, and we would expect a lower wage dispersion in more concentrated employment markets.

3.2 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 simultaneously wages and employer concentration, 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 new firms' entry. 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 operate in the opposite direction, biasing the OLS estimates upward.

Instrumental Variable Estimation To address the endogeneity of the HHI, we implement an IV strategy following Azar et al. (2020) and Rinz (2020). Specifically, we instrument the HHI with the average log inverse number of employers, $\ln(1/N)$ in other geographic markets within the same 3-digit industry and year. Conceptually, the instrument exploits variation in employer's concentration driven by changes in national-level concentration and not by market-specific changes. Formally, we define the instrument as Z_{cjt}:

$$Z_{cjt} \equiv \frac{1}{(C_j - 1)} \sum_{c' \neq c \in C_j} \ln\left(\frac{1}{N_{c'jt}}\right) \tag{4}$$

where C_j denotes the number of commuting zones where industry j is active, and $N_{c'jt}$ is the number of employers in each commuting zone c' and industry j.

For the baseline specification (3), the IV strategy works as follows. In the first stage, we predict market HHI based on the instrument Z_{cjt}:

$$\ln \text{HHI}_{cjt} = \gamma_1 Z_{cjt} + \gamma_2 X_{icjt} + \delta_{cj} + \delta_{ct} + \delta_i + \epsilon_{icjt} \tag{5}$$

In the second stage, we regress the log average wage earned by employees working in firm i in market cj in year t, y_{icjt}, on predicted ln HHI, $\widehat{\ln \text{HHI}}_{cjt}$, firm labor productivity, and fixed effects:

$$y_{icjt} = \beta_1 \widehat{\ln \text{HHI}}_{cjt} + \beta_2 X_{icjt} + \delta_{cj} + \delta_{ct} + \delta_i + \varepsilon_{icjt} \tag{6}$$

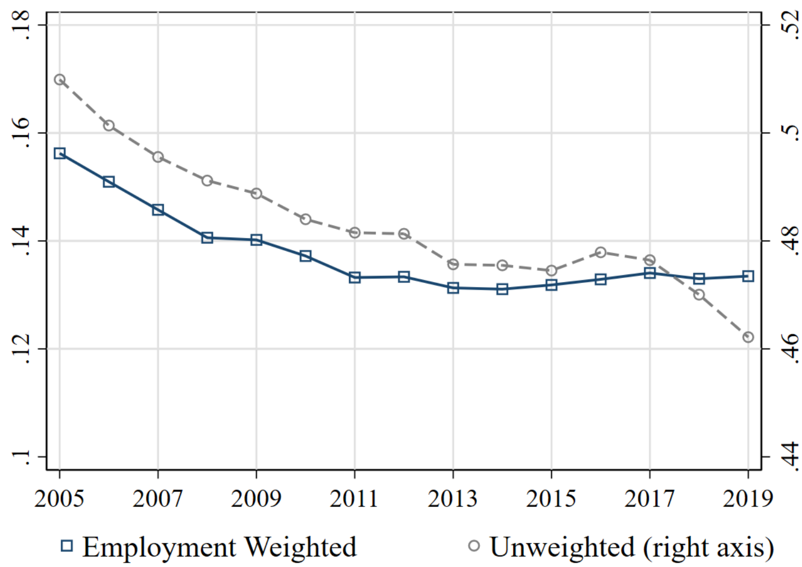
Exclusion Restriction and Identification Equation (6) recovers the causal effect of labor market concentration under the assumption that the instrument affects average wages only through its effect on HHI. We note that this assumption may fail if demand or supply shocks are correlated across markets. We account for this possibility including commuting zone-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 Employment Concentration in Chile

Aggregate employment concentration trajectories. Figure 2 plots the evolution of the employment HHI over 2005-2019. On average, the labor market concentration shows a slight decrease but has remained relatively stable over the period.[3] While the unweighted HHI decreased slightly from 2005 to 2019, from 0.510 to 0.462, the weighted HHI decreased somewhat more sharply from 0.156 in 2005 to 0.13 in 2011 and remained constant from 2011 to 2019.

[3]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% in the U.S. manufacturing sector during 1978-2016.

Figure 2. Evolution of the Employment HHI in Chile, 2005-2019



Notes: The figure shows the evolution of the HHI in Chile since 2005. The dashed-gray (right axis) line takes simple averages of the HHI across markets in each year. The solid-blue line (left axis) weights the HHI by the employment of each market. We define markets at the level of 3-digit ISIC industries and commuting zones.

Figure 3 checks the robustness of the patterns documented in Figure 2 under different labor market definitions. For all definitions, the employment-weighted HHI falls slightly or remains close to constant. The evolution of the weighted HHI when defining the labor market at the 4-digit ISIC and commuting zone level is presented in Rinz (2020) and shows a similar trend. He documents a decline from 0.20 in 1980 to 0.145 in 2015, with small changes from 2000.

Figure 3. Evolution of the Employment HHI in Chile under different labor market definitions

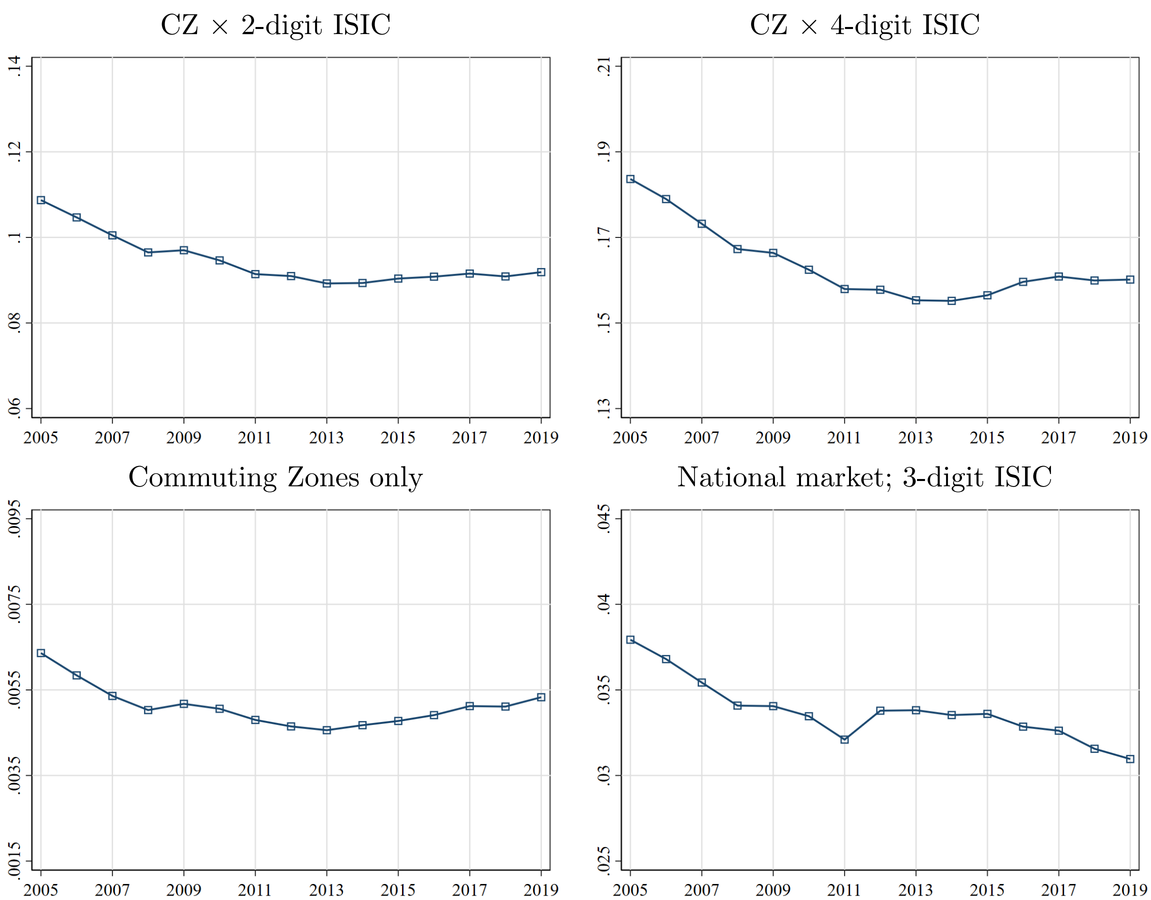


Table 3 divides the markets into quintiles according to their concentration and presents a characterization of these markets. A sizeable difference in average can be observed in average concentration between quintiles. As expected, the more concentrated the market, the lower the average number of firms in each market. However, on average, these firms in concentrated markets have more employment per firm than firms in less concentrated markets, suggesting that these firms are unlikely to be small firms or start-ups in small markets. Finally, wages increase slightly, and labor productivity decreases slightly across HHI quintiles.

Table 3. Concentration and Labor Market Characteristics

	HHI Quintiles				
	Q1	Q2	Q3	Q4	Q5
Average HHI	0.099	0.280	0.505	0.784	0.995
	(0.067)	(0.085)	(0.091)	(0.094)	(0.014)
Average number of firms	107	14	5	2	1
	(304.3)	(29.36)	(10.27)	(4.28)	(0.49)
Average employment	2,028	321	188	91	40
	(9,373)	(1,287)	(1,234)	(355.6)	(248.5)
Average employment per firm	19.0	22.9	37.6	45.5	40.0
Average log wages	12.56	12.59	12.63	12.65	12.72
	(0.24)	(0.26)	(0.32)	(0.35)	(0.48)
Average labor productivity	15.92	15.88	15.90	15.85	15.81
	(0.54)	(0.63)	(0.93)	(0.95)	(1.39)

Notes: The table lists the summary statistics for the variables used in the paper's baseline analysis sample. For each local labor market, the average concentration over years was taken and used to divide markets into quintiles. All averages are unweighted and nominal variables are expressed in millions of 2013 Chilean pesos. Standard deviation in parenthesis.

5 Employment Concentration and Wages

OLS Results. Table 4 presents OLS results from estimating the baseline wage equation (3). Columns 1 to 3 report unweighted results, while column 4 weight observation by firm employment. Across specifications, we find a positive and statistically significant coefficient on labor productivity, suggesting that firms with more productive workers pay higher wages. Columns 1 and 4 exploit variation in earnings and employment concentration within labor markets, including year and industry-commuting zone fixed effects. Columns 2 and 5 include firm fixed effects to control for differences in average labor composition across firms and a more flexible specification for the year effects, interacting them with CZ fixed effects to control for local-level demand and supply shocks. Thus, these estimates are based on employment concentration variation within firms and labor markets. Finally, columns 3 and 6 present our preferred specifications, where we include industry trends and industry controls (at the 4-digit ISIC level) to account for industry-specific shocks

Table 4. Labor Market Concentration and Wages: OLS Results Regressions

	Unweighted			Employment Weighted		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	ln $\bar{y}_{fcjt}$	ln $\bar{y}_{fcjt}$	ln $\bar{y}_{fcjt}$	ln $\bar{y}_{fcjt}$	ln $\bar{y}_{fcjt}$	ln $\bar{y}_{fcjt}$
ln(HHI$_{cjt}$)	-0.00238	-0.00109	-0.00172*	0.0155*	-0.00870**	-0.00696**
	(0.00219)	(0.00145)	(0.00104)	(0.00808)	(0.00357)	(0.00282)
ln(labor productivity$_{fcjt}$)	0.126***	0.0316***	0.0315***	0.151***	0.0280***	0.0273***
	(0.00548)	(0.00109)	(0.00108)	(0.0168)	(0.00174)	(0.00160)
Year FE	✓			✓		
Industry-CZ FE	✓	✓	✓	✓	✓	✓
CZ-year FE		✓	✓		✓	✓
Firm FE		✓	✓		✓	✓
Industry trends			✓			✓
Industrial controls			✓			✓
Observations	2,056,608	2,056,608	2,056,608	2,056,608	2,056,608	2,056,608

Notes: All regressions are run at the firm-level through OLS. HHI are computed at the 3-digit industry-commuting zone level. Regressions (1)-(3) are unweighted, while regressions (4)-(6) are weighted by firm-level employment. Standard errors (in parentheses) are clustered at the 3-digit industry-commuting zone level.Key: *** significant at 1%; ** 5%; * 10%.

Results in Table 4 underline the relevance of controlling for idiosyncratic firm differences when analyzing the relationship between employment concentration and wages. In columns 1 and 4, we find non-significant or positive coefficients on labor market concentration, suggesting that employment concentration does not dampen wages.[4] However, when we include firm fixed-effects, and industrial trends and controls, these coefficients turn negative. These results suggest that, while firms in more concentrated labor markets hire a higher proportion of high-wage workers, they tend to pay them lower wages when labor market concentration increases. Employment-weighted coefficients (columns 4 to 6) are significantly larger than unweighted coefficients (columns 1 to 3), suggesting that large firms extract a higher proportion of the surplus when employment concentration increases. The estimated coefficient implies a moderate effect of labor concentration: Increasing labor concentration in one standard deviation decreases wages by 1.5%.

Instrumental Variable Results. As we discuss in section 3.2, variation in the HHI may be driven by third factors also affecting average wages. Table 5 present 2SLS results using the

[4] 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.

one-leave-out HHI described in section 3.2 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 shows the corresponding first stages. With the exception of column 6, we obtain first-stage F-statistics substantially above the Stock-Yogo critical value of 16.4 for 10% maximal IV bias. The coefficient on the instrument is positive and highly significant. While the coefficient remains relatively unchanged when adding firm and CZ-year fixed effects, it declines by about half when adding industry trends and controls, which is natural considering that the instrument precisely exploits industrial variation in other geographies. Overall, the positive first-stage coefficient implies that labor market concentration in a particular industry-CZ is positively correlated with the labor market concentration of the same industry in the rest of CZ of the country. The magnitude of the first-stage coefficient implies that a one percent increase in the HHI of other municipalities is associated with an increase in HHI that varies between 0.28 and 0.72 and 1.8%.

Finally, panel C shows the second-stage results. The estimated coefficient on labor market concentration is negative and highly significant in all specifications that include firm fixed effects. This suggests that firms pay lower wages when employment concentration increases. 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 changes in employment concentration on earnings and with similar magnitudes for the weighted and unweighted cases. A one-standard deviation in the HHI leads to a reduction of wages between 0.9 percent (unweighted coefficients) and 1.0 percent (weighted coefficients). As in the case of OLS regressions, weighting observation by firm employment substantially increases coefficients.

Table 5. Labor Market Concentration and Wages: 2SLS Regressions Results

	Unweighted			Employment Weighted		
	(1)	(2)	(3)	(4)	(5)	(6)
A. Reduced form Dependent variable:	$\ln \bar{y}_{fcjt}$	$\ln \bar{y}_{fcjt}$	$\ln \bar{y}_{fcjt}$	$\ln \bar{y}_{fcjt}$	$\ln \bar{y}_{fcjt}$	$\ln \bar{y}_{fcjt}$
$\ln(1/N_{-cjt})$	-0.00884*	-0.0177***	-0.0165***	-0.0201	-0.0396***	-0.0308**
	(0.00518)	(0.00464)	(0.00377)	(0.0156)	(0.0103)	(0.0137)
$\ln(\text{labor productivity}_{fcjt})$	0.126***	0.0316***	0.0315***	0.151***	0.0280***	0.0273***
	(0.00548)	(0.00109)	(0.00108)	(0.0168)	(0.00170)	(0.00159)
B. First Stage Dependent variable:	$\ln(\text{HHI}_{cjt})$	$\ln(\text{HHI}_{cjt})$	$\ln(\text{HHI}_{cjt})$	$\ln(\text{HHI}_{cjt})$	$\ln(\text{HHI}_{cjt})$	$\ln(\text{HHI}_{cjt})$
$\ln(1/N_{-cjt})$	0.725***	0.660***	0.391***	0.585***	0.507***	0.278***
	(0.0738)	(0.0665)	(0.0707)	(0.0910)	(0.0772)	(0.0898)
$\ln(\text{labor productivity}_{fcjt})$	0.00117**	0.00220***	0.00163***	-0.000791	-0.00356	-0.00634***
	(0.000465)	(0.000630)	(0.000384)	(0.00154)	(0.00286)	(0.00236)
First stage F-Statistic	96.5	98.5	30.6	41.3	43.2	9.6
C. Second Stage Dependent variable:	$\ln \bar{y}_{fcjt}$	$\ln \bar{y}_{fcjt}$	$\ln \bar{y}_{fcjt}$	$\ln \bar{y}_{fcjt}$	$\ln \bar{y}_{fcjt}$	$\ln \bar{y}_{fcjt}$
$\ln(\widehat{\text{HHI}_{cjt}})$	-0.0122	-0.0268***	-0.0421***	-0.0343	-0.0781***	-0.111**
	(0.00755)	(0.00792)	(0.0125)	(0.0281)	(0.0248)	(0.0531)
$\ln(\text{labor productivity}_{fcjt})$	0.126***	0.0317***	0.0316***	0.151***	0.0277***	0.0266***
	(0.00548)	(0.00109)	(0.00107)	(0.0168)	(0.00173)	(0.00158)
Year FE	✓			✓		
Industry-municipality FE	✓	✓	✓	✓	✓	✓
Municipality-year FE		✓	✓		✓	✓
Industry trends		✓	✓		✓	✓
Industrial controls			✓			✓
Firm FE			✓			✓
Observations	2,056,608	2,056,608	2,056,608	2,056,608	2,056,608	2,056,608

Notes: All regressions are run at the firm-level through OLS. HHI are computed at the 3-digit industry-commuting zone level. Regressions (1)-(3) are unweighted, while regressions (4)-(6) are weighted by firm-level employment. Standard errors (in parentheses) are clustered at the 3-digit industry-commuting zone level. Key: *** significant at 1%; ** 5%; * 10%.

Within-Firm Distributional Effects The previous results indicated that concentration is associated to lower average earnings at the firm level. However, this average effect can be associated to different patterns. First, it can hide a relevant degree of heterogeneity, with varying effects across workers with different characteristics. As discussed earlier, supply elasticities and bargaining power might vary across different types of workers. Second, the reduction of firm level average wages could also reflect in the firm composition of worker types, as firms increase their share of low wage workers.

On the one hand, high-skill workers might have higher bargaining power with the firm as they might be harder to substitute, which could buffer their wages from the effects of concentration, but at the same time, might have more firm-specific human capital that might limit their mobility. Low-skill workers, on the other hand, might be easier to replace but might also be more capable of finding a new job easily and are protected by the minimum wage restrictions.

We start by investigating 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 6 show the results, focusing on our preferred specification with market, municipality-year, and firm fixed-effects. We only show second-stage results.

Table 6. Concentration and within-firm wage distribution

	—— Percentiles Within-Firm Wage Distribution ——				
Dependent Variable	P10	P25	P50	P75	P90
			Unweighted		
ln(HHI$_{cjt}$)	-0.0186	-0.0256**	-0.0349***	-0.0572***	-0.0748***
	(0.0122)	(0.0129)	(0.0128)	(0.0159)	(0.0199)
ln(labor productivity$_{fcjt}$)	0.0449***	0.0421***	0.0357***	0.0239***	0.0107***
	(0.00147)	(0.00137)	(0.00117)	(0.00102)	(0.000880)
First Stage F-Statistic	30.6	30.6	30.6	30.6	30.6
			Employment weighted		
ln(HHI$_{cjt}$)	-0.0845*	-0.0844	-0.121**	-0.144**	-0.140**
	(0.0445)	(0.0525)	(0.0584)	(0.0627)	(0.0715)
ln(labor productivity$_{fcjt}$)	0.0194***	0.0235***	0.0279***	0.0315***	0.0333***
	(0.00126)	(0.00148)	(0.00164)	(0.00214)	(0.00250)
First Stage F-Statistic	9.6	9.6	9.6	9.6	9.6
Observations	2,056,608	2,056,608	2,056,608	2,056,608	2,056,608

Notes: All regressions are run at the firm-level through OLS. HHI are computed at the 3-digit industry-commuting zone level. All regressions control for industry-commuting zone FE, commuting zone-year FE, industry trends, industrial controls and firm FE. Standard errors (in parentheses) are clustered at the 3-digit industry-commuting zone level. Key: *** significant at 1%; ** 5%; * 10%.

Table 6 show the results for unweighted and weighted regressions. Two results stand out. First, in unweighted regressions, labor productivity correlates more strongly with wages on the bottom of the firm's wage distribution than with wages at the top. This suggests that firms' top wages can be 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 a relatively higher bargaining power when setting wages than low wage workers. However, this does not happen in weighted regressions, suggesting that these forces are weaker in larger firms. This might reflect that sorting patterns are stronger in larger firms.

Turning to our variable of interest, we observe that labor market concentration affects workers differently depending on their position within the wage distribution. In the unweighted regressions, 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 (-0.0186) is less than half of the average value estimated in Table 5. However, as we move upwards in the wage distribution, the negative effect of labor concentration increases (in absolute value) strongly. The estimated coefficient for wages in the 90th percentile is almost three times as large as the one for wages in the 25th percentile. The same pattern holds true for weighted regressions, although differences are smaller.

These results suggest that more concentrated markets are associated with less within-firm dispersion. We address this in Table 7. For unweighted regressions, different measures of dispersion, such as the relative wages across different percentiles and the within firm standard deviation of earnings, decrease as concentration grows. Although the point estimates for weighted regressions are also negative, they are not significant, suggesting that these distributional effects are smaller for larger firms.

Table 7. Concentration and wage dispersion

	—— Within-Firm Wage Dispersion ——			
Dependent Variable	P50/P10	P90/P10	P90/P50	St. Dev.
	Unweighted			
ln(HHI$_{cjt}$)	-0.0163**	-0.0562***	-0.0399***	-0.0228***
	(0.00777)	(0.0193)	(0.0153)	(0.00736)
ln(labor productivity$_{fcjt}$)	-0.00918***	-0.0342***	-0.0250***	-0.0140***
	(0.000537)	(0.00137)	(0.000909)	(0.000514)
First Stage F-Statistic	30.6	30.6	30.6	30.6
	Employment weighted			
ln(HHI$_{cjt}$)	-0.0366	-0.0559	-0.0193	-0.0109
	(0.0323)	(0.0510)	(0.0334)	(0.0151)
ln(labor productivity$_{fcjt}$)	0.00853***	0.0139***	0.00542***	0.00396***
	(0.00111)	(0.00226)	(0.00175)	(0.000858)
First Stage F-Statistic	9.6	9.6	9.6	9.6
Observations	2,056,608	2,056,608	2,056,608	2,056,608

Notes: All regressions are run at the firm-level through OLS. HHI are computed at the 3-digit industry-commuting zone level. All regressions control for industry-commuting zone FE, commuting zone-year FE, industry trends, industrial controls and firm FE. Standard errors (in parentheses) are clustered at the 3-digit industry-commuting zone level. Key: *** significant at 1%; ** 5%; * 10%.

One final question is whether these patters are associated to changes in composition, so that firms in more concentrated market have a different mix of worker types, or directly by an heterogeneous impact of concentration on different types of workers. To address this, given that we have no information on worker education, we estimate a fixed effects model of earnings, controlling for worker age, tenure in the firm, and the labor productivity of the firm:

$$w_{ijt} = \alpha_t + \gamma_0 * age_{it} + \gamma_1 * tenure_{ijt} + \mu_i + \phi * f(y_j(i,t)) + \varepsilon_{ijt} \tag{7}$$

where $f(y_j(i,t))$ is a second-order polynomial of the firm's labor productivity. We use the worker fixed effect, μ_i, to rank workers into quintiles. This provides a proxy of the market's valuation (in terms of earnings) of the skills/abilities of any given worker, net of the effects associated to being employed in a firm with a given productivity and having a given tenure.

Table 8 uses the skill proxies to calculate the average skill level at each firm, and relate it to the market level of concentration. We can see that, as expected, more productive firms have workers with higher average skills, a result that seems consistent with the notion of sorting.

However, the effects of concentration on skills are less clear. Unweighted regressions indicate that there is no effect, so the skill composition of firms in more concentrated markets does not seem to change. Therefore, this suggests that the reduction in average wages is not driven by a shift in the composition of employment towards less skilled workers. Results are slightly different when we look at weighted regressions, as there seems to be evidence that higher concentration is linked to a reduction in the skill composition of firms. Therefore, it seems to be the case that larger firms that exert market power hire relatively less high skilled workers.

Finally, Tables 9 and 10 look at the effects of market concentration for the average firm-level wages of each skill quintile. In unweighted regressions, the effects of concentration hurt the earnings of all types of workers, but have a stronger effect on high-skilled individuals. The estimated coefficient for workers on the top skill quintile is -0.085, twice as large as the coefficients associated to workers in the bottom half of the distribution. In weighted regressions, differences in the point estimates across quintiles are much smaller, suggesting that in larger firms the negative effects of concentration are more muted. This is consistent with the previous results that found that the impact of concentration on within firm dispersion was smaller in larger firms.

To sum up, in our baseline specification we find that low-wage workers are relatively less affected than high-wage workers by employment concentration. As we discussed earlier, this may be due to a more elastic labor supply of these workers, which have more general skills and can move more easily across industries in a given commuting zone, or use their outside option of moving to informality. Additionally, the earnings are closer to the legal minimum wage, and are likely to become bounded by it, especially in smaller firms that pay lower overall wages. 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.

Table 8. Regressions: Average skill level

	Unweighted			Employment Weighted		
	(1)	(2)	(3)	(4)	(5)	(6)
Second Stage						
Dependent variable:	$\bar{s}_{fcjt}$	$\bar{s}_{fcjt}$	$\bar{s}_{fcjt}$	$\bar{s}_{fcjt}$	$\bar{s}_{fcjt}$	$\bar{s}_{fcjt}$
$\ln(\widehat{\text{HHI}_{cjt}})$	0.00192	0.00516	0.000987	-0.0321	-0.0527**	-0.0348*
	(0.00798)	(0.0104)	(0.00816)	(0.0196)	(0.0223)	(0.0199)
ln(labor productivity$_{fcjt}$)	0.0641***	0.0153***	0.0151***	0.0598***	0.0105***	0.00996***
	(0.00368)	(0.000885)	(0.000867)	(0.00708)	(0.00212)	(0.00205)
Year FE	✓			✓		
Industry-municipality FE	✓	✓	✓	✓	✓	✓
Municipality-year FE		✓	✓		✓	✓
Industry trends			✓			✓
Industrial controls			✓			✓
Firm FE		✓	✓		✓	✓
Observations	2,056,608	2,056,608	2,056,608	2,056,608	2,056,608	2,056,608

Notes: All regressions are run at the firm-level through OLS. HHI are computed at the 3-digit industry-commuting zone level. Regressions (1)-(3) are unweighted, while regressions (4)-(6) are weighted by firm-level employment. Standard errors (in parentheses) are clustered at the 3-digit industry-commuting zone level.Key: *** significant at 1%; ** 5%; * 10%.

Table 9. Concentration and average wages across skill levels

	Unweighted				
Group	Q1	Q2	Q3	Q4	Q5
	Dependent Variable: $\ln \bar{y}^{g}_{fmjt}$				
$\ln(\widehat{\text{HHI}_{cjt}})$	-0.0460***	-0.0417***	-0.0593***	-0.0710***	-0.0850***
	(0.0127)	(0.0124)	(0.0164)	(0.0180)	(0.0198)
ln(labor productivity$_{fcjt}$)	0.0118***	0.0142***	0.0170***	0.0207***	0.0307***
	(0.000425)	(0.000471)	(0.000569)	(0.000577)	(0.000833)
First Stage F-Statistic	24.8	23.4	24.1	24.1	21.3
Observations	1,613,839	1,282,622	1,298,955	1,252,402	1,009,115

Notes: All regressions are run at the firm-level through OLS. HHI are computed at the 3-digit industry-commuting zone level. All regressions control for industry-commuting zone FE, commuting zone-year FE, industry trends, industrial controls and firm FE. Standard errors (in parentheses) are clustered at the 3-digit industry-commuting zone level. Key: *** significant at 1%; ** 5%; * 10%.

Table 10. Concentration and average wages across skill levels

	Employment Weighted				
Group	Q1	Q2	Q3	Q4	Q5
	A. Dependent Variable: ln $\bar{y}^{g}_{fmjt}$				
$\ln(\widehat{\text{HHI}}_{cjt})$	-0.0933*	-0.0701	-0.0815	-0.103**	-0.109**
	(0.0490)	(0.0535)	(0.0510)	(0.0482)	(0.0508)
ln(labor productivity$_{fcjt}$)	0.00994***	0.0134***	0.0150***	0.0169***	0.0232***
	(0.00107)	(0.00131)	(0.00115)	(0.00115)	(0.00162)
First Stage F-Statistic	8.7	8.6	8.7	8.8	8.4
Observations	1,613,839	1,282,622	1,298,955	1,252,402	1,009,115

Notes: All regressions are run at the firm-level through OLS. HHI are computed at the 3-digit industry-commuting zone level. All regressions control for industry-commuting zone FE, commuting zone-year FE, industry trends, industrial controls and firm FE. Standard errors (in parentheses) are clustered at the 3-digit industry-commuting zone level. Key: *** significant at 1%; ** 5%; * 10%.

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 wages. This relationship is heterogeneous: High-wage workers' earnings are impacted more negatively than low-wage workers' earnings, leading ultimately to a negative relationship between within-firm earnings dispersion and concentration.

Our results shed light on the effect of economic concentration in developing economies. However, we underline the need of more research to understand whether the patterns observed in the Chilean labor markets hold more generally in other emerging economies.

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Online Appendix

Labor Market Concentration and Workers Outcomes: Evidence from Chile

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A Additional Results

Robustness checks

1. Robustness Checks (1): Relationships considered
2. Robustness Check (2): Geography
3. Robustness Check (3): Labor market definition (by industry)
4. Robustness Check (4): Functional form (level of HHI and instrument)
5. Robustness Check (5): Using ln(average wage) instead of average(ln wage)
6. Robustness Check (6): Controlling for average skill composition
7. Robustness Check (7): Specification in differences
8. Robustness Check (8): Labor market definition (by geography)

Table A.1. Robustness check 1: Relationship considered

	Unweighted			Employment Weighted		
	(1)	(2)	(3)	(4)	(5)	(6)
Relationships included	All	Baseline	Length > 12 months	All	Baseline	Length > 12 months
$\ln(\widehat{\mathrm{HHI}}_{cjt})$	-0.0462***	-0.0448***	-0.0389***	-0.106**	-0.111**	-0.111**
	(0.0129)	(0.0129)	(0.0126)	(0.0531)	(0.0531)	(0.0520)
$\ln(\text{labor productivity}_{fcjt})$	0.0324***	0.0324***	0.0309***	0.0268***	0.0266***	0.0257***
	(0.00114)	(0.00114)	(0.00110)	(0.00158)	(0.00158)	(0.00154)
First stage F-Statistic	17780.0	16960.8	15230.1	316.7	312.8	301.8
Observations	2,052,189	2,012,990	1,923,074	2,052,189	2,012,990	1,923,074

Notes: All regressions are run at the firm-level through OLS. HHI are computed at the 3-digit industry-commuting zone level. All regressions control for industry-commuting zone FE, commuting zone-year FE, industry trends, industrial controls and firm FE. Standard errors (in parentheses) are clustered at the 3-digit industry-commuting zone level. Key: *** significant at 1%; ** 5%; * 10%.

Table A.2. Robustness check 2: Geography

	Unweighted			Employment Weighted		
	(1)	(2)	(3)	(4)	(5)	(6)
Geography:	All	Excluding RM	Excluding small CZ	All	Excluding RM	Excluding small CZ
$\ln(\widehat{\mathrm{HHI}}_{cjt})$	-0.0448***	-0.0441***	-0.0451***	-0.111**	-0.0684**	-0.111**
	(0.0129)	(0.0128)	(0.0131)	(0.0531)	(0.0274)	(0.0533)
$\ln(\text{labor productivity}_{fcjt})$	0.0324***	0.0233***	0.0325***	0.0266***	0.0195***	0.0266***
	(0.00114)	(0.000636)	(0.00114)	(0.00158)	(0.00127)	(0.00159)
First stage F-Statistic	16932.8	6556.3	16765.6	312.8	493.1	310.2
Observations	2,012,990	923,227	1,994,680	51,475,325	15,931,990	51,249,045

Notes: All regressions are run at the firm level through OLS. HHI is computed at the 3-digit industry-commuting zone level. All regressions control for industry-commuting zone FE, commuting zone-year FE, industry trends, industrial controls, and firm FE. Standard errors (in parentheses) are clustered at the 3-digit industry-commuting zone level. Key: *** significant at 1%; ** 5%; * 10%.

Table A.3. Robustness check 3: Industry disaggregation

	Unweighted			Employment Weighted		
	(1)	(2)	(3)	(4)	(5)	(6)
Industry disaggregation for HHI	4-digits ISIC	3-digits ISIC	2-digits ISIC	4-digits ISIC	3-digits ISIC	2-digits ISIC
$\ln(\widehat{\mathrm{HHI}}_{cjt})$	-0.0455***	-0.0420***	-0.0349***	-0.143**	-0.111**	-0.0809
	(0.0127)	(0.0121)	(0.0132)	(0.0608)	(0.0516)	(0.0609)
$\ln(\text{labor productivity}_{fcjt})$	0.0316***	0.0316***	0.0316***	0.0266***	0.0266***	0.0270***
	(0.00105)	(0.00105)	(0.00105)	(0.00157)	(0.00158)	(0.00160)
First stage F-Statistic	12319.3	16662.7	18578.1	284.1	311.9	355.8
Observations	2,056,419	2,056,440	2,056,492	51,467,609	51,468,363	51,471,061

Notes: All regressions are run at the firm level through OLS. All regressions control for industry-commuting zone FE, commuting zone-year FE, industry trends, industrial controls, and firm FE. Standard errors (in parentheses) are clustered at the industry-commuting zone level. Key: *** significant at 1%; ** 5%; * 10%.

Table A.4. Robustness check 4: Functional form

	Unweighted		Employment Weighted	
Measure	$\ln(\text{HHI}_{cjt})$	HHI_{cjt}	$\ln(\text{HHI}_{cjt})$	HHI_{cjt}
Instrument	Geometric mean	Arithmethic mean	Geometric mean	Arithmethic mean
	(1)	(2)	(3)	(4)
Labor market concentration	-0.0448***	-0.732**	-0.111**	1.523
	(0.0129)	(0.312)	(0.0531)	(6.317)
$\ln(\text{labor productivity}_{fcjt})$	0.0324***	0.0325***	0.0266***	0.0288***
	(0.00114)	(0.00115)	(0.00158)	(0.00584)
First stage F-Statistic	91.5	29.8	24.5	0.6
Observations	2,012,990	2,012,990	2,012,990	2,012,990

Notes: All regressions are run at the firm level through OLS. HHI is computed at the 3-digit industry-commuting zone level. All regressions control for industry-commuting zone FE, commuting zone-year FE, industry trends, industrial controls, and firm FE. Standard errors (in parentheses) are clustered at the 3-digit industry-commuting zone level. Key: *** significant at 1%; ** 5%; * 10%.

Table A.5. Robustness check 6: Controlling for skill composition

	Unweighted		Employment Weighted	
	(1)	(2)	(3)	(4)
$\ln(\widehat{\text{HHI}}_{cjt})$	-0.0399***	-0.0455***	-0.110	-0.0864*
	(0.0144)	(0.0118)	(0.0740)	(0.0442)
$\ln(\text{labor productivity}_{fcjt})$	0.0920***	0.0231***	0.0965***	0.0196***
	(0.00303)	(0.000604)	(0.0119)	(0.00135)
$\ln(\text{average skill}_{fcjt})$	0.604***	0.632***	0.908***	0.705***
	(0.0115)	(0.00706)	(0.0281)	(0.0128)
First stage F-Statistic	15275.8	15718.3	299.6	279.4
Industry-municipality FE	✓	✓	✓	✓
Municipality-year FE	✓	✓	✓	✓
Industry trends	✓	✓	✓	✓
Industrial controls	✓	✓	✓	✓
Firm FE		✓		✓
Observations	2,012,990	2,012,990	2,012,990	2,012,990

Notes: All regressions are run at the firm-level through OLS. HHI are computed at the 3-digit industry-commuting zone level. Standard errors (in parentheses) are clustered at the 3-digit industry-commuting zone level. Key: *** significant at 1%; ** 5%; * 10%.

Table A.6. Robustness check 7: Controlling for skill composition

	Unweighted	Weighted
	$\Delta\ln\, \bar{y}_{fcjt}$	$\Delta\ln\, \bar{y}_{fcjt}$
$\Delta\ \ln(\widehat{\text{HHI}}_{cjt})$	-0.0614*	-0.158
	(0.0314)	(0.114)
Δ ln(labor productivity$_{fcjt}$)	0.0194***	0.0185***
	(0.000681)	(0.00276)
First stage F-Statistic	1573.5	34.4
Observations	1,531,187	1,531,187

Notes: All regressions are run at the firm-level through OLS. HHI are computed at the 3-digit industry-commuting zone level. Both regressions control for commuting zone-year FE, industry trends and industrial controls. Standard errors (in parentheses) are clustered at the 3-digit industry-commuting zone level. Key: *** significant at 1%; ** 5%; * 10%.

Table A.7. Robustness check 8: Local market definition (geography)

	Unweighted			Employment Weighted		
	(1)	(2)	(3)	(4)	(5)	(6)
Industry disaggregation for HHI	Municipality	Commuting Zone	Province	Municipality	Commuting Zone	Province
$\ln(\widehat{\text{HHI}}_{cjt})$	-0.0314***	-0.0421***	-0.0195*	-0.0982***	-0.111**	-0.146
	(0.00807)	(0.0125)	(0.0111)	(0.0339)	(0.0531)	(0.135)
ln(labor productivity$_{fcjt}$)	0.0317***	0.0316***	0.0316***	0.0268***	0.0266***	0.0264***
	(0.000609)	(0.00107)	(0.00108)	(0.00134)	(0.00158)	(0.00174)
First stage F-Statistic	16279.3	16696.4	13007.7	526.1	311.8	147.7
Observations	2,056,515	2,056,556	2,056,567	2,056,515	2,056,556	2,056,567

Notes: All regressions are run at the firm-level through OLS. All regressions control for industry-commuting zone FE, commuting zone-year FE, industry trends, industrial controls and firm FE. Standard errors (in parentheses) are clustered at the industry-commuting zone level. Key: *** significant at 1%; ** 5%; * 10%.