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Abstract*

We examine the impact of changes in local labor market concentration on two components of income inequality in Mexico: local wage shares and labor income inequality. Combining data from the Economic Census and the Population and Housing Censuses, we analyze the mechanisms that drive the relationship between concentration and labor income inequality by considering heterogeneities across groups of workers (skilled and unskilled) and sectors. In line with previous studies for developed countries and with the emerging literature on monopsony power, we first show that a higher level of concentration is associated with reductions in skilled and unskilled workers' wages. Furthermore, the elasticities are relatively similar. Second, there is sectoral heterogeneity as, for manufacturing, unskilled workers' wages decrease more, while skilled workers do not exhibit any reduction. On the other hand, for services, the effects are similar for the two groups. Third, unionization plays a countervailing role against monopsony power, as in highly-unionized sectors, the effect of higher concentration on wages is null, and this is consistent with a higher level of bargaining power. Even though the effects of labor market concentration on inequality are not sizeable, the impact on wages for skilled and unskilled workers is significant.

JEL clasifications: J23, J31, J42
Keywords: Inequality, Monopsony, Labor markets

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1 Introduction

Over the past four decades, the Labor Income Share (LIS), as a proportion of GDP, has been decreasing across countries. Even after its sustained decline, the LIS in most OECD countries remains above 50% of GDP, while in Latin America, it has decreased from 42% in 1970 to 36% in 2016 (Abeles et al., 2017). If wealth and capital income are more unequally distributed than labor endowments and labor income, a decrease in the labor income share will tend to increase inequality in personal income (Daudey and García-Peñalosa, 2007; García-Peñalosa and Orgiazzi, 2013).

The international literature attributes the decline of LIS to several potentially interrelated causes, including the expansion of international trade and import shocks (Elsby et al., 2013); increasing economic integration (Dao et al., 2017); technical change and the falling cost of capital relative to the cost of labor (Karabarbounis et al., 2014); and the role of the decline in product market competition and the emergence of "superstar" firms that concentrate increasing shares of sales and value-added within industries (Autor et al., 2017, 2020).

An emerging strand of research investigates the relationship between labor market concentration and changes in the LIS, as part of a broader resurgence of interest in monopsony power in labor markets (Ashenfelter et al., 2010; Manning, 2011, 2021; Card, 2022). Monopsony power in the labor market can be defined as the employers' ability (acting unilaterally or collusively) to set wages in a labor market, as opposed to taking market wages as given, paying workers less than their marginal productivity. That is, there is "a 'markdown' in wages that reflects an employer's ability to extract a monopsony surplus without fear that workers will leave for another job that pays their full marginal product" (Steinbaum, 2018). An employer's monopsony power is proportional to the (inverse) elasticity of the labor supply to his or her firm (Matsudaira, 2014). It can arise from cooperative behavior among a small number of firms in a labor market, and/or when frictions in job search and geographic mobility are significant (Rinz, 2022).

Our research focuses on the relationship between monopsony power in the labor market, labor's share of income, and inequality in the personal distribution of labor income in Mexico from 2000 to 2015. Combining data from the Economic Census, the Population and Housing Censuses, household surveys, as well as administrative and geographic information system data, we evaluate the impact of changes in local labor market concentration on two components of total income inequality: the local wage shares; and labor income inequality. We define local labor markets as the combination of industry and geography, where industry is determined at the NAICS-3 digits level, and the geographic extension of the labor market is defined by the commuting zones. We then explore the mechanisms that drive the relationship between concentration and labor income inequality by analyzing heterogeneities across groups of workers (skilled and unskilled) and sectors.[1] As previously explained, we would expect workers in the left tail of the earnings distribution to be more negatively affected by increases in labor demand concentration as they face more job search frictions along with higher costs in terms of geographic mobility. To analyze these relationships, we use panel data instrumental variable estimations.

Mexico is a relevant case study for several reasons. Inequality in the distribution of personal income, once one adjusts for property rents, has increased over time (Del Castillo, 2015), while the LIS has reduced from 35% to 27% over the last forty years (without considering mixed incomes) (Samaniego Breach, 2014). Adjusting for labor earnings of self-employed workers, Ibarra and Ros (2019) show a decline from 36% to 30% between 1995 and 2015. Today, Mexico has the lowest LIS among OECD countries, lower than Chile and Greece, and less than half that of Denmark (Samaniego Breach, 2014). We observe decreases in the LIS at the same time as the country exhibits a very low growth rate, suggesting that decreasing labor incomes should play an important role in the decline of the LIS. Meanwhile, product market concentration is relatively low at the national level, but it has been increasing in most sectors over time and shows high levels of variation across regions (Rodríguez-Castelán et al., 2023).

To the best of our knowledge, no similar in-depth analyses for labor market concentration exist,[2] but there are grounds to suspect that monopsony power may be sizeable. First, the geographical mobility of labor is relatively low: the Aggregate Crude Migration Intensity calculated by Bell et al. (2015) shows that 5-year geographical mobility in Mexico is quite low, at 13% of the Population, and similar to that of China with its *hukou* system, compared to 46% in the US, 37% in Chile, and more than 20% in Costa Rica, Peru, and Uruguay. This suggests that labor may be more inelastically supplied compared to other settings. Second, Mexico is characterized by highly distorted markets and misallocation of resources (labor, capital, and financing, among others) (Hsieh and Klenow, 2014; Levy, 2018; Misch and Saborowski, 2018; Bloom et al., 2022; Iacovone et al., 2022), which may increase search and relocation costs and reinforce the impacts of labor market concentration.

[1] Skills are proxied both as white and blue-collar workers and as labor with high school or more against workers with a lower educational level.

[2] Oseguera Sauri (2022) analyzes concentration in the Mexican labor market between 2004 and 2014, finding no evidence suggesting monopsony power.

Distinct from previous literature, this research contributes first by providing the first analysis of national and local trends in monopsony power in Mexico, proxied by labor market concentration. We calculate local labor market concentration in Mexico over the 2000-2015 period, as a proxy for monopsony power.

Second, while most existing studies concentrate on developed countries, presenting relatively low levels of distortions and barriers to economic activity, this research disentangles the relationship between concentration, the labor income share, and income inequality in a middle-income country with significantly distorted markets and misallocation of resources, as is the case in many developing countries, where concentration and misallocation might reinforce each other (Hsieh and Klenow, 2014; Levy, 2018; Misch and Saborowski, 2018).

Third, we explicitly control for informality as a measure of market tightness. This represents a more suitable measure than the unemployment rate for the case of a developing country like Mexico, considering that the informal sector concentrates more than half of total employment (56.3% in 2019, according to the National Survey of Employment, ENOE).

This paper uncovers three key results. First, we show that average real wages do decrease with labor market concentration, which points towards the presence of monopsony power at the local level. On average, the change in wages associated with competition shifts appears similar for low-skilled and high-skilled workers, regardless of the definition.

Second, digging further into sectoral heterogeneity, we find that low-skilled workers exhibit a higher wage reduction when concentration increases in manufacturing. On the other hand, the wages of skilled workers do not show significant changes in this sector. In contrast, for services, the effects on wages are quite similar for low-skilled and skilled workers.

Third, despite the fact that the labor market in Mexico has been historically characterized by strong corporatist relations between unions, employers, and governments, we show that a higher level of bargaining power can compensate for the negative effects of monopsony power on wages. Splitting the sample according to the level of unionization of the sectors, we show that the average effects we observe are mainly driven by sectors with a low unionization level. In contrast, sectors with a higher proportion of workers participating in unions do not exhibit significant effects on wages.

The paper is structured with a short summary of the recent literature on monopsony power in Section 2. We describe the methods, definitions, and data used throughout the paper in Section 3. Section 4 focuses on the relationship between labor market concentration, wages for different skill groups, the wage share, and inequality. Finally, Section 5 concludes.

2 Literature Review

The labor income share (LIS) is frequently used as a proxy for income inequality (Karabarbounis et al., 2014). According to these authors, and consistent with Shorrocks (1982): (*i*) changes in total income inequality mainly depend on changes in the labor income share (LIS); (*ii*) changes in within-labor and within-capital inequality; and (*iii*) the degree to which the highest wage earners coincide with the highest capital earners.

Evidence for the US shows that employers are highly concentrated in labor markets (Ransom and Sims, 2010; Staiger et al., 2010; Yeh et al., 2022, among others), and that concentration has a robust negative effect on posted wages (Azar et al., 2020) and on earnings from administrative data (Benmelech et al., 2022). Brooks et al. (2021) study monopsony, either by a single employer or a collusive group of producers, in China and India. They find falling labor market concentration over time, but also a significant adverse impact of monopsony power on wages and on LIS. In contrast, Berger et al. (2022) find no evidence of labor market concentration leading to lower LIS in the United States.

Meanwhile, monopsony power in the labor market may affect total income inequality, not only through its influence on the LIS, but also by changing the shape of the earnings distribution and within-labor inequality. Webber (2015) found that increased employer power in the labor market increases inequality in the overall earnings distribution. Others have considered the effects of monopsony power on specific groups of workers, finding, for instance, that it reduces the wages of immigrants in Germany (Hirsch and Jahn, 2015), and increases the gender wage gap in both Germany (Hirsch et al., 2010) and the US (Webber, 2016).

Rinz (2022) documents the degree to which monopsony power is prevalent within local labor markets in the United States and estimates its effects on labor earnings outcomes across the earnings distribution, within and across demographic groups. He finds that increased local concentration reduces earnings and increases inequality, both within and across different socioeconomic groups. He also finds that the increase in inequality is mainly driven by the reduction in wages of the bottom 10% of the earnings distribution, rather than by the increase in wages of the 90th earnings percentile. That is, labor market concentration lowers wages at the bottom of the earnings distribution, presumably because labor supply elasticity is lower among less-skilled workers, as a result of more frictions in job search and lower geographic mobility. Similarly, Bassier (2019), shows for South Africa substantial wage-setting power by employers and that differences in labor supply elasticities, across gender and income groups, explain significant shares of both the gender wage gap and the wage gap between workers in the middle and the bottom of the income distribution.

3 Methods

3.1 Data and Measurement

3.1.1 Local Labor Markets

We define local labor markets as a combination of industry and geography, following Azar et al. (2022). Ideally, we would have preferred to define occupations rather than industries, similar to those authors. However, the equivalent information we have (online vacancies) is hardly representative of the characteristics of occupations at the local level; if anything, only for large Metropolitan Areas.

Considering these data constraints, we defined industry at the NAICS-3 digits level.[3] To determine the geographic extension of the labor market, we use the commuting zones calculated by Blyde et al. (2020). Through this procedure, which is explained in more detail in Online Appendix A, all Mexican municipalities were assigned to 780 commuting zones.

3.1.2 Labor Market Concentration

We measure concentration in the local labor market using the Herfindahl-Hirschman Index (HHI) of employment, which in the Cournot model of oligopsonistic competition is directly related to wages: an increase in the HHI leads to a proportionate increase in the gap between the marginal productivity of labor and wages, i.e., Pigou's rate of exploitation or the wage markdown (Boal and Ransom, 1997).

[3] We also analyzed the database at the NAICS-4 digits level, but the matching between the Economic Censuses and the Population and Housing Censuses is poor. For robustness purposes, we also constructed the database at the NAICS-2 digits level and estimated the same equations.

The Herfindahl-Hirschman Index (HHI) is calculated based on the share of employment of all employers in that market.We calculate the HHI in market m (that is, the combination of sector and commuting zone) and time t as:

$$HHI_{m,t} = \sum_{j=1}^{J} s_{j,m,t}^{2} \tag{1}$$

where $s_{j,m} \in (0, 100)$ is the market share of firm j in market m. The market share of a firm, in a given market and time, is defined as the employment of the firm in that market and time, divided by total employment by all firms in that market and time. Each market *m* is defined, as above, as the combination of occupation and geography.

As an alternative measure of labor market concentration, we use the share of total employment of the five largest firms in a given market and time. The use of these two measures of labor market concentration makes our analysis complementary to Rodríguez-Castelán et al. (2023), who use the HHI in the product market and the share of sales of the largest five firms to estimate product market concentration in 56 metropolitan areas of Mexico.

As shown in Figure 1, on average, concentration, measured as the HHI for the labor market, has been declining over the period of analysis. A similar trend is observed in the case of the share of top five firms. Indeed, these two variables have a correlation of 0.95. In Figure 2, we analyze the whole distribution for these variables. As the figure shows, the distribution of the concentration indicators moves slightly to the left, indicating an increase in competition or a reduction in concentration over the period.

It is important to note that even though, on average, we observe reductions in labor market concentration, as shown in Figure 3, some sectors (panel b) like couriers, telecommunications, and air transportation, have shown persistent increases in labor market concentrations, while for others (panel a) competition has increased.

3.1.3 Outcome Variables

The main outcome variables that we analyze are the wage share at the local level (measured as total wages over value-added), the mean labor income in the local labor market (separated by skilled and unskilled), and measures of labor income inequality (90/10 earnings ratio: the ratio of the 90^{th} percentile of the earnings distribution to the 10^{th} percentile, plus 50/10 and 90/50 ratios).[4] Finally, as an alternative measure, we use the Gini coefficient of labor income.[5]

As shown in Figure 4, the wage share declined between 2000 and 2015, particularly between 2000 and 2005. In the last 10 years, it has remained relatively stable. For the inequality measures, regardless of the measures we analyze, reductions are observed in Figure 5, except for the lower part of the distribution (P50/P10). In this case, there is an increase in inequality, and then a decrease is observed. In Figure 6, we analyze the whole distribution of inequality measures, and it is clear that inequality has reduced over the period of analysis.

3.1.4 Data Sources

We combine data from the Economic Census, the Population and Housing Census, and household surveys, as well as administrative and geographic information system data, to build a panel of municipalities for the period 2000-2015.

To analyze concentration through the HHI index, we use the 1999, 2004, 2009, and 2014 Economic Censuses from the National Institute of Statistics and Geography (INEGI in Spanish), which include establishment-level data for manufacturing, services, and commerce. We also use these data to analyze average wages for the formal sector, categorized by skilled and unskilled workers (proxied as white and blue-collar workers).

For the analysis of labor income and inequality, we use the 2000 and 2010 Population and Housing Censuses, INEGI, along with the Inter-censal surveys for 2005 and 2015, which are representative at the municipality level.[6] Considering that this survey's main objective is not the collection of income and wages data, we compare and validate these data with what is reported in the National Survey of Occupation and Employment (ENOE in Spanish). Data on municipal characteristics are readily available through the Population Census and the State and Municipality System of Databases (Sistema Estatal y Municipal de Bases de Datos, INEGI) as well as information from the National Council of Population (CONAPO).

[4]See Ibarra and Ros (2019) for further explanation on how to calculate the wage share.

[5]The measure of labor income inequality has the caveat that we can only calculate it using the Population and Housing Censuses for 2000 and 2010, as well as the 2015 Inter-censal survey. Therefore, we also use data from the Economic Census to analyze average wages for the formal sector broken down by skilled and unskilled workers (proxied as white and blue-collar workers).

[6]The inter-censal survey for 2005 does not provide information on labor income. Therefore, we use the specification from equation (5) to use the data for 2015. For robustness purposes, we also estimate the equation using only 2000 and 2010.

Given that most of our outcomes are related to the labor market, we use the National Occupation and Employment (ENOE) survey to calculate additional measures at the sectoral level, such as unionization, and to test the validity of the measures we calculate using the Population and Housing Censuses. As an additional source to analyze wages' distribution, we use data from the Economic Census, which provides information for formal workers.[7]

3.2 Identification Strategy

We use a fixed-effects estimator to control for time-invariant unobserved heterogeneity across labor markets. The fixed effects estimator allows us to measure the effect of firm concentration on changes in inequality *within* labor markets. However, even conditional on fixed effects or other observed market characteristics, changes in labor market concentration may not occur exogenously, but rather arise from other economic changes that also affect the earnings distribution.

To address the concern for a potentially endogenous increase in labor market concentration, we adopt an instrumental variables strategy similar to Azar et al. (2022) and Rinz (2022): we instrument for the HHI in each labor market in each year using the employment-weighted average HHI in other geographic markets for the same occupation and time. This strategy identifies the effects of local concentration on earnings outcomes, using variation in local concentration that is driven by national-level changes in employment over time, and not by potentially endogenous changes in employment within a particular local market. The instrument is:

$$\overline{HHI}_t^{-m} = \frac{\sum_{z \neq m} HHI_{z,t} \cdot Emp_{z,t}}{\sum_{z \neq m} Emp_{z,t}} \tag{2}$$

where m is a specific labor market, z is the set of the other geographic markets for the same occupation excluding market m, and t denotes time. The first stage regression is:

$$\log\left(HHI_{m,t}\right) = \log\left(\overline{HHI}_t^{-m}\right)\gamma + \delta X_{m,t} + \alpha_m + \theta_t + \omega_{m,t} \tag{3}$$

where $X_{m,t}$ is a set of controls which includes, among other variables, the share of em-

[7]See Online Appendix Table F1 for descriptive statistics of all the variables included in the analysis.

ployment that is informal as a measure of market tightness;[8] α_m are market fixed effects; θ_t are year fixed effects; and $\omega_{m,t}$ is the error term. The effect of concentration on our labor income outcomes of interest (mean labor income, wage share, and labor income inequality) is estimated as:

$$\log\left(y_{m,t}\right) = \log\left(H\hat{H}I_{m,t}\right)\beta + \delta X_{m,t} + \alpha_m + \theta_t + \varepsilon_{m,t} \tag{4}$$

where $H\hat{H}I_{m,t}$ is the fitted values from the first stage regression, and $\varepsilon_{m,t}$ is the error term. The coefficient of interest is β, that is, the elasticity of each labor income outcome with respect to local labor market concentration. Alternatively, we estimate this equation in differences to account for periods of different length:

$$\frac{\Delta\log\left(y_{m,t}\right)}{n} = \frac{\Delta\log\left(H\hat{H}I_{m,t}\right)}{n}\beta + \delta\frac{\Delta X_{m,t}}{n} + \theta_t + \varepsilon_{m,t} \tag{5}$$

A potential threat to identification is endogenous labor mobility. To address this, within the set of controls, we include a measure of net migration rates in the commuting zone. As a robustness check, we also replicate the analysis including only incumbent workers, that is, workers who have not moved to or from the local labor market over the period of analysis.

Similar to Azar et al. (2022), this leave-one-out approach, which has been used in many papers, such as Nevo (2001), deals with potential productivity shocks at the local market level (sector-commuting zone combination in our case). However, it does not prevent our identification strategy from being threatened by some sector-specific national-level productivity shocks that could alter firm concentration as well as wages.

Another potential threat to the identification of our main equation is labor supply shocks that could directly affect labor outcomes (wages) and, consequently, could lead to fewer firms hiring and, therefore, a higher market concentration. In this case, we would be facing a problem of reverse causality. However, under our instrumental variable framework, and after controlling for migration, which could affect labor supply in a local market, this risk is not eliminated but significantly mitigated.

[8] A typical measure of market tightness is the unemployment rate; however, the unemployment rate in Mexico is very low and varies relatively little across the country. In contrast, the informal sector concentrates more than half of total employment (56.3% in 2019 according to the National Survey of Employment, ENOE) and its prevalence varies substantially across space.

Finally, as Goldsmith-Pinkham et al. (2020) argue, our leave-one-out instrumental variable approach shares some similarities with the Bartik shocks. Firstly, identification depends crucially on the exogeneity of the shares (employment weights). Secondly, we assume that labor markets are independent and, therefore, ignore spatial correlation. However, through spillovers, spatial correlation poses the challenge that there could be a direct effect of our instrument over the labor outcome variables. Still, as explained by Azar et al. (2022), our instrument is still plausibly more exogenous than the own local labor market concentration and is less likely to be correlated with local labor market productivity shocks. Following these authors, we test the robustness of our results in two different ways. We implement the plausibly exogenous methodology developed by Conley et al. (2012), and estimates bounds for our instrument, assuming full exogeneity and some deviations from exogeneity based on the range from the reduced form effect. Secondly, we test an alternative instrument based on Azar et al. (2022) that uses the average of the $\ln\left(\frac{1}{N}\right)$ for the same industry and time in the rest of the commuting zones. As shown in Figure E1 of the Online Appendix, this new instrument, which has the property of not depending on labor market shares, is highly correlated with our main instrument (a correlation of 0.85). Therefore, our results do not change by using this alternative instrument.

As an additional robustness check, we analyze the impact on labor income inequality of the entry of new large firms in a local labor market, in the same spirit as Atkin et al. (2018).[9] We compare local labor markets with the entry of new large firms to local labor markets for the same occupation in comparable commuting zones, where no significant shock to the market structure occurs over the period. We control for non-random firm location by estimating the probability that a large firm would locate in labor market m as a function of place characteristics that affect firms' production and transaction costs. We then use the predicted probability as weight in a difference-in-difference (DiD) equation estimating the impact on labor income inequality of the entry of a new large employer, comparing "treated" local labor markets with similar "non-treated" local labor markets, following a methodology similar to Cazzuffi et al. (2017).

[9] These authors also have the advantage that the entry of Walmart to a local market represents a competition shock both in the labor and the product markets.

4 Results

4.1 The Wage Share, Wages in the Formal Sector, and Labor Market Concentration

Using the information at the labor market level (NAICS-3digits-zone) from the Economic Censuses only, we analyze the relationship between wage share and concentration (measured as HHI and the share of the top five firms). As shown in panel (a) of Figure 7, this relationship appears to be non-linear, with the wage share initially increasing slightly with concentration and then showing the decreasing relationship we would expect, according to the literature. However, it is important to point out that, as depicted in Figure 2, most of the density of the distribution is concentrated where the correlation is negative. We test this in a regression framework, appropriately instrumenting for concentration (see equations 2 and 3) in column (1) of Table 1.[10] Our results indicate that, indeed, the relationship is negative and that a 10 percent increase in concentration, as measured by the HHI, is associated with a 0.4 decrease in the wage share (measured as a percentage). This magnitude is relatively low.

In panel (b) of Figure 7, we show the correlation between wages and labor market concentration, splitting by white-collar and blue-collar workers. As depicted in the figure, wages tend to be lower for blue-collar workers for markets of similar concentration. However, the slope is very similar for these two groups of workers. In columns (2) and (3) of Table 1, we show that a 1% increase in concentration is related to a 0.8% decrease in blue-collar as well as in white-collar workers. Initially, we would have expected that white-collar workers should have more bargaining power and, therefore, would exhibit a lower coefficient in absolute terms. However, even though the coefficient is lower, the difference seems economically negligible. When we analyze the skill premium in column (4), we observe that there is a small increase derived from these small differences. Moreover, the results are robust to using the share of the top 5 firms in each market as a measure of labor market concentration (columns 5-8 of Table 1).

As pointed out by Esquivel and Rodrıguez-López (2003), this definition (white vs. blue-collar) is commonly used as a proxy for skilled and unskilled in the literature, mainly due to data limitations. As these authors argue, citing Gonzaga et al. (2006), this associ-

[10]The OLS results are shown in Table F2 of the Online Appendix. The magnitudes in the OLS equations are lower for the wages equation, but the signs and differences across groups (white and blue-collar) remain the same. In Table F3 of the Online Appendix we present the first stage of the instrumental variable estimation.

ation might be imperfect and could lead to differences against the skills definition using educational levels. We will test this in the following section by using education instead.

We further test our results' robustness by considering the long period that takes the first Economic Census in our panel (1999) and the last one (2014). As shown in Table F8 of the Online Appendix, the results do not change.

4.2 Inequality Measures and Skilled and Unskilled wages

In Table 2, we show the estimates following equation 5. We can define more precisely skilled and unskilled workers using education, as we combine data from the Economic Censuses and the Population and Housing Censuses. Although most studies for developed countries define as "skilled" those workers with college or more, in Mexico's case, we use high school or more. The reason is that the average level of education for people aged 25-64 is still under 10 years of schooling, according to the National Income Expenditure Survey 2018. Figure 8 compares changes in the distribution of wages over time between this skilled-unskilled definition based on educational attainment and the proxy we used in the previous section (white-collar vs. blue-collar). As shown in the figure, blue-collar workers and unskilled seem to evolve in a similar way, as the density for 2013 is shifted to the right, indicating improvements in the wage structure for this type of workers. On the other hand, the density for skilled workers shifts slightly to the left, while in the case of white-collar workers, it seems to reduce its variance and, in any case, to shift slightly to the right. This might be an indicator that among white-collar workers, there is a portion of unskilled workers who have improved their wages over time.

As shown in columns (2) and (3) of Table 2, using this new definition of skilled-unskilled, once we instrument and control for market tightness (using the informality rate in each market) and migration net flows, still the coefficients for skilled and unskilled are very similar. However, the coefficients are much lower in comparison with Table 1. This result can be explained, besides the inclusion of controls, by the difference in the definition of skilled-unskilled and the change in the sample, as we are now only considering those markets that match between the Economic Census and the Population and Housing Censuses. Additionally, the two statistical projects have differences in their scope, as the Economic Census focuses on establishments with a specific location, while the Housing and Population Census includes a broader definition of labor.

Considering how increasing labor market concentration affects inequality, we observe in Figure 9 that, unconditionally, a higher level of concentration is positively correlated with more inequality, regardless of the inequality measure we choose. We test these different measures in a regression framework in columns (5) to (8) of Table 2. In all cases, except for the Gini coefficient, we observe positive and significant coefficients, indicating that lower competition is correlated with more inequality. Nevertheless, the magnitudes of the coefficients are relatively low, considering the mean and standard deviations of these inequality variables (see Online Appendix Table F1). This is consistent with what we observe in terms of wages, as coefficients for unskilled workers are slightly higher than those for skilled, leading to a tiny increase in inequality. Once again, our results are robust to the measure of concentration as for the share of the top 5 firms (lower panel of Table 2), the results are similar.

Similar to what we did in the previous section, we test the robustness of our results by estimating a long-term specification, which only includes data from the 2000 and 2010 Population and Housing Censuses. The main reason for estimating such a specification is to account for the fact that the quality of the Census data is higher than the one from the 2015 Inter-Censal survey and, thus, measurement error could be biasing our results. In Table F9 of the Online Appendix, we show these estimates. The results are very similar to the ones shown in Table 2.[11]

4.3 Is Migration Driving Our Results?

A potential threat to our results is that people's movement across regions could be affecting our results. Labor markets are dynamic, and changes in the composition of the labor force could affect wages and, thus, inequality. So far, we have accounted for this movement by controlling for net migration flows. To further address this potential issue, we estimate in Table 3 a specification that only includes incumbents. We take advantage of a variable in the Population and Housing Censuses that reports whether the individual lived in the same municipality five years ago. We aggregate this information at the local zone level using Blyde et al. (2020) and define wages and inequality just for incumbents.

As shown in columns (1) and (2) of Table 3, once we consider only incumbents, wages' effects continue to be similar between skilled and unskilled workers. Still, the elasticities are higher (around -0.20 against -0.12 in Table 2). The results on inequality measures are once again positive, small, and even not significant in some specifications.

[11] In Table F10 of the Online Appendix we analyze wages per hour instead of monthly wages, the elasticities for wages are slightly lower, but the main results hold.

4.4 Sectoral Heterogeneity

An important consideration for this analysis is the particular characteristics of the different sectors included in our sample. As previously mentioned, in particular, the services sector exhibits a higher level of distortions and misallocation compared to manufacturing (See Misch and Saborowski, 2018, 2020). Therefore, we performed the same regression analysis as in Tables 2 and 3, but we split the sample into manufacturing and services (also including retail and wholesale commerce).

For the manufacturing sector (upper panel of Table 4), we observe that unskilled workers' wage elasticity is much higher than the one observed for skilled wages. A 1% increase in labor market concentration is associated with a 0.45% decrease in unskilled wages. Furthermore, the elasticity for skilled wages is much lower and not significant. Accordingly, the effects on inequality are much higher. This result is consistent with the theoretical prediction that skilled workers have more bargaining power, at least in this less distorted sector. On the other hand, the elasticities are smaller for services, in line with our previous results, and very similar between skilled and unskilled workers. Therefore, the average effects we observe for wages in Table 2 are mainly driven by services firms.

Once again, we test our results' robustness using the top 5 firms' share as our labor market concentration measure. As shown in Table F11 of the Online Appendix, the results are quite similar.

4.5 Does Bargaining Power Compensate for Monopsony Power?

According to the literature, the negative effects that monopsony power imposes on wages can be counteracted by the workers' bargaining power (Manning, 2013). One mechanism by which this bargaining power is exerted is through unions, positively affecting wages (Breda, 2015) and reducing wage inequality (Card et al., 2017, 2020). Accordingly, in developed countries, several studies show that the decline in unions has contributed to the increase in inequality.[12] In fact, the gradual de-unionization observed in most countries is considered among the mechanisms that increased the skill-premium during the 1980s and 1990s (Brambilla, 2018).

Nevertheless, the institutional environment in Mexico differs from that in developed countries, which may imply that unionization is not necessarily an efficient mechanism to affect the wage structure and wage inequality in the Mexican labor market. Historically,

[12] Card et al. (2017, 2020) present an excellent review of the literature.

since the 1930s with the creation of the Confederation of Mexican Workers (the largest confederation of labor unions in Mexico), the labor market in Mexico has been characterized by strong corporatist relations between unions, employers, and governments. These corporatist relations were useful to gain labor control, granting economic and political benefits to unions' leaders, at the expense of limited benefits for workers (Tilly, 2014). One example of this is "employer protection contracts," widely implemented in Mexico since the 1980s, in which the union leaders sign a contract with the employer (typically signed before the opening of factories or establishments), minimizing employees' benefits and reducing the possibility of future changes in the collective contract (Tilly, 2014; Escobar Toledo, 2019). This, in turn, may reduce the workers' bargaining power. Hence, it is interesting to study whether bargaining power can compensate for monopsony power in Mexico.

To analyze whether the effects on wages differ according to bargaining power (proxied by unions), we use the National Survey of Occupation and Employment (ENOE in Spanish). We take the data for 2005, which is the earliest period available, and calculate the share of people in each NAICS-3 digits sector that is part of a union. We further validate this data using other periods of ENOE. Then, we construct a dummy variable that takes the value of one if the sector has a share of workers participating in unions above the median and a value of zero if the share is below the median.

In Table 5, we show the results split using this dummy variable. When we analyze sectors with a low level of unionization in the upper panel, the effects of higher labor concentration on wages are still negative and significant. In this case, we do observe differences between skilled and unskilled workers. In these sectors, where there is very low protection from unions, skilled workers appear to have higher bargaining power and, therefore, a lower elasticity to increasing labor market concentration. On the other hand, we observe no significant effect of a higher HHI over wages for highly-unionized sectors. That is, unions provide bargaining power for both skilled and unskilled workers. Even so, inequality appears to increase marginally due to labor composition.

4.6 Are the Effects Symmetric?

An important consideration in terms of the heterogeneity of results has to do with the idea of whether monopsony power operates equally regardless of whether labor market concentration increases or decreases.

To analyze this, we separate the cases of increases in labor market concentration (as measured by the HHI index) and decreases. In Figure 10, we show the results for all the labor market outcomes of interest. The results indicate that there are indeed asymmetries in the effects, as decreases in labor market concentration drive most of the average results we have observed in previous tables. That is, reductions in labor market concentration lead to wage increases of a higher magnitude. This could be due to the fact that in the presence of monopsony power in the local labor market, wages are already low. Therefore, firms have a limited scope for reducing wages further in the context of increasing labor market concentration.

4.7 The Role of Informality

Even though we explicitly control for the informality rate as a measure of market tightness in our main estimations, in a country where, on average, 60% of the labor force works in the informal sector, it is worth exploring whether informality has a more prominent role.

A first approach to accounting for the role of informality is to focus on the particularly high share of microenterprises in Mexico. According to the 2014 Economic Census, not only 95% of all the establishments are microenterprises (with ten employees or less), but furthermore, 42% are one-employee establishments. These are not all informal firms, but as they behave similarly, can be considered as a proxy of informality. To analyze the role of these firms, first, we estimate a specification in which we control for the share of this type of firm in each local labor market. Our results, shown in Online Appendix Tables F4 and F5, indicate that the results do not change against Tables 1 and 2.

A second analysis we performed to account for these small firms' participation was to re-estimate all our specifications without considering one-employee firms in the calculation of our labor market concentration measure and the corresponding instrument. As Tables F6 and F7 of the Online Appendix show, once again, our results essentially do not change by excluding firms of this size from the calculation of the HHI.

As a third strategy to analyze the role of informality, we explicitly account for it in our model by adding an interaction between labor market concentration and informality. The purpose behind this specification is to analyze if there is heterogeneity according to the level of informality in the local labor market.

It is essential to highlight that, a priori, the direction of this interaction is not clear as it depends on the sources of informality. Following the informality literature (Ulyssea, 2020) and specifically for the case of Mexico, there is no consensus on the sources of these high levels of informality. Some authors mention the case of segmented or dualistic markets, which in the Harris-Todaro framework are characterized by a group of unskilled rural workers that are waiting to be absorbed by a modern formal sector (See Rauch, 1991; Straub, 2005; Loayza and Sugawara, 2009, for further information on this kind of models). Under this hypothesis, high informality would further increase monopsony power.

Contrary to the theoretical predictions of segmented market models, as pointed out by Rauch (1991) and Maloney (2004), reverse mobility (from the formal to the informal sector) has been observed, which made necessary the development of other lines of research. Among them, there is the one in favor of integrated markets, where workers voluntarily opt out of the formal labor market. As Maloney (2004) argues, these kinds of models are consistent with a life-cycle model where workers acquire some abilities from the formal market and then, move to the informal market to pursue their own business and assume all the risks associated with this decision. Under this model, an increasing informality would at least partially mitigate the effects of monopsony power on wages.

As (Maloney, 2004) and Esquivel and Ordaz-Díaz (2008) argue, evidence for Mexico on whether the integrated or the segmented markets hypothesis is correct has not provided conclusive results.[13]

Table 6 shows the results comparable to Table 2, including the interaction between local market concentration and informality. As shown in the table, for the case of unskilled workers, the interaction is positive, indicating that informality attenuates the effect of local market concentration for this type of worker. Therefore, the result is consistent with the hypothesis of integrated markets where workers can opt out of the formal market and, therefore, the effects of monopsony power are lower.

4.8 Analyzing Competition Shocks through Entrants

In this section, we analyze the case of large firms entering local markets. To do this, we take advantage of the algorithm and panel of establishments constructed by Busso et al. (2018) using 1999, 2004, 2009, and 2014 Economic Censuses.[14] With these data, we identify those firms that appear in one Census but not in the previous one. Even though we are well aware that the matching between Censuses is not perfect, we assume that larger firms have a lower probability of not being found in the previous Census, therefore, reducing the threat of a measurement error. Only 3.63% of the observations (labor markets) in the

[13]For example, Arias et al. (2010) find evidence in favor of segmented markets for Mexico.
[14]See Busso et al. (2018) for the details on the matching algorithm and the panel construction.

sample have large entrants. Among them, 60% have only one establishment entering the market, 15% have two establishments, and some local markets even have 194 new establishments, which is plausible considering the time gap between Economic Censuses.

To make the control and treatment groups comparable, we use propensity score matching methods. Following Mu and Van de Walle (2011), Jalan and Ravallion (1998), and Cazzuffi et al. (2017), we estimate the probability that a labor market is treated based on local characteristic and the national growth of each NAICS-3 digits sector and recover the Inverse Propensity Score (IPS). Then, we estimate our outcome equation weighting by the IPS. This allows controlling for self-selection of firms into labor markets based on observable characteristics. Table F12 of the Online Appendix shows the result of the probit equation, in which we consider characteristics such as population, distance to the capital city, utilities, and infrastructure, and the share of employment in manufacturing. This is a very general specification that could work for most sectors, although, for example, sectors such as the food industry might consider other factors like cultivated land, irrigation, etc.

Table 7 shows the results using both the dummy variable, which indicates whether there are new entrants in the labor market, and the discrete variable with the number of entrants. The latter variable intends to account for the intensity of treatment. As the table shows, a competition shock (proxied by new entrants) is correlated with a higher wage level for skilled workers. Having new entrants is associated with a 0.5% increase in skilled-workers' wages. In the specification that uses the number of entrants, each additional establishment's effect is statistically significant, but the magnitude is negligible.

However, the same is not observed for unskilled wages. The effects of entrants on these wages are not statistically significant. Therefore, it is not surprising that even as increasing competition positively affects skilled workers' wages, inequality rises due to the differential effects across the skills distribution.

To test the robustness of these results, in Table F13 of the Online Appendix, we estimate a specification in which we also include the initial level of the HHI as a control variable. As shown in the table, the results essentially do not change.

4.9 Robustness Tests

Thus far, the specifications we used to analyze labor market concentration and outcomes have relied on the use of fixed effects, which focus on within effects. Therefore, it is relevant to test whether these results hold in a pooled regression setting; that is, when we consider both within and between effects.

In Table F14, we re-estimate Table 1 as a pooled regression, controlling for time and sector effects. The results are similar but smaller in magnitude for wages, but slightly higher in absolute terms for the reduction in the wage share. Once again, the reduction in wages for blue-collar workers is higher. This is consistent with a higher level of inequality, and thus, a lower wage share, as the gap between white and blue-collar wages increases in the context of increasing labor market concentration.

When we consider a pooled regression framework to replicate the results from Table 2, we observe that most of the results are similar, except for the result on skilled wages that now are not significant (see Table F15 of the Online Appendix). Nevertheless, because unskilled wages do decrease, inequality and the wage share increase as in the previous tables. The similarity between the fixed effects and pooled regressions indicates that it is not a matter of within or between effects what is driving our results.

We performed additional robustness tests, such as constructing the whole database at the NAICS-2 digits level-zone instead. This approach has the advantage of reducing the case of small cells (a low number of observations within each labor market) as we now include a broader set of sectors in each labor market. The results do not change much under this setting.[15]

Additionally, considering the geographical heterogeneity observed in Mexico, we analyzed if our results could be driven by large cities such as CDMX and its Metropolitan Area, Monterrey, and Guadalajara. We re-estimated Tables 1 and 2, excluding CDMX and its Metropolitan Area and, alternatively, excluding all the large cities. As shown in Tables F16, F17, and F18 of the Online Appendix, our results are robust to excluding these cities from the sample.

5 Conclusions

This paper analyzed labor market concentration at the local level and its relationship with labor outcomes, such as wages of skilled and unskilled workers, the wage share, and inequality measures. To do this, we merged information from the Economic Censuses and the Population and Housing Censuses between 2000 and 2015 and aggregated it at the labor market level, trying to narrowly define commuting zones and sectors.

[15]Results defining labor markets at the NAICS-2 digits sector-zone are not shown here, but are available upon requests.

Our main results showed that a higher level of local labor market concentration is indeed associated with lower wages, which is consistent with the results observed in the literature on monopsony power (Azar et al., 2019, 2022). Furthermore, on average, we did not find differences in the elasticities of wages of skilled and unskilled workers over labor market concentration. This was observed even when we focus only on incumbents, to avoid the problems associated with labor mobility.

However, there is heterogeneity in the effects across sectors. For manufacturing, we observed that the reductions of unskilled wages due to increased labor concentration are larger than average, while no significant change was observed for skilled workers. This is consistent with the theoretical prediction that more skilled workers have more bargaining power, while unskilled workers face more job search frictions along with higher costs in terms of geographic mobility. In contrast, firms in the services sector are the ones driving average results, as they have similar elasticities for the wage of skilled and unskilled workers.

To investigate whether bargaining power has a role in the relationship between local labor market concentration and wages, we analyzed sectors with a higher proportion of workers participating in unions. We found that the coefficients on the wage elasticities to local labor market concentration are no longer significant for these sectors. This reflects unions' bargaining power, which compensates for the adverse effects of increasing local concentration over wages. On the other hand, for lowly-unionized sectors, the negative effects on wages remain but are now larger for unskilled workers who, as previously mentioned, tend to have lower bargaining power and face more job search frictions.

Considering the importance of informality in the case of Mexico, besides controlling for it, we explored its role in monopsony power. Our results supported the hypothesis of integrated markets behind informality, as in local labor markets with more informality, the negative effects of labor market concentration on unskilled wages were attenuated.

We further analyzed the effect of competition shocks (proxied by large firms' entry into local labor markets) on labor outcomes. We found that while for skilled workers, a higher level of competition improves wages, for unskilled workers, entrants' effects are not statistically significant. Unsurprisingly, inequality rises due to the differential effects across the skills distribution.

In general, we find the effect of labor market concentration on inequality to be low in magnitude, which is due to the fact that, on average, wages for skilled and unskilled workers have similar coefficients. However, it is worth noting that the effects on wages tend to be significant. Therefore, it is important to take into consideration the heterogeneity across local labor markets in terms of sectoral differences and the bargaining power of employees. An important caveat of our results in terms of wages is that they do not consider idiosyncratic amenities, which could have different valuations for workers beyond their salaries (See Naidu and Posner, 2022). Unfortunately, the data available do not allow us to account for this.

Turning to policy alternatives to address monopsony power, as Naidu and Posner (2022) point out, in contrast with product markets, antitrust might be insufficient and not feasible for labor markets, especially at the local level. Since antitrust focuses on mergers and anticompetitive behavior, monopsony in the labor market is out of its scope. Monopsony power can, however, be addressed through labor law. In Mexico's case, despite the advances that have been made, there still exist opportunities for further improvement.

Considering the mechanisms we discussed, which could be at work in the case of the relationship between labor market concentration and wages, the easiest approach in terms of policy responses is to tackle search frictions. As the literature points out, workers may not be aware of the jobs available and therefore decide towards these lower-wage jobs. In this sense, improving the information available for training and job decisions could significantly reduce these frictions.[16]

Another policy that is mentioned in the literature is increasing the minimum wage. In fact, Mexico experienced such an increase in 2019. Nevertheless, some authors are skeptical about the scope of this policy, considering that it would only affect workers in the lower tail of the distribution, as well as the potential effects on unemployment. Therefore, the scope of this policy is also limited. Future studies should still analyze whether the rise of the minimum wage had any impact on labor market monopsony power, taking advantage of the increments during the previous years.

Finally, some authors mention among the alternatives, legal support to unions or significant increases in unionization, mainly in the services sector (See, for instance, Card et al., 2020). This policy seems unfeasible in the case of Mexico for at least two reasons. First, similar to other countries, Mexico has undergone a profound process of deunionization. Secondly, the inherent corruption of some of the largest unions, as well as their use for political purposes, has undermined the credibility of these organizations as a mechanism of fostering bargaining power for employees. Unless independent unions

[16]Naidu and Posner (2022) mention Glassdoor, a company that includes employees' rating of a variety of jobs and employers, as an example of actions that might help to reduce search frictions.

emerge, employer protection contracts are efficiently regulated, and the institutional environment of unions improves, it will be challenging to foster bargaining power for workers through strengthening unions.

In conclusion, policies to face monopsony power in local labor markets are complex and may require a combination of different approaches.

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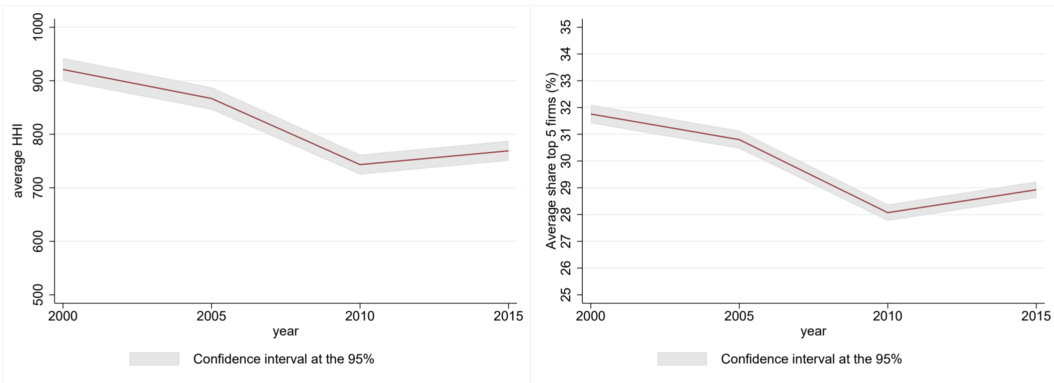
Figures

Figure 1: Evolution of Firm Concentration

(a) Mean HHI

(b) Share top 5 firms (%)

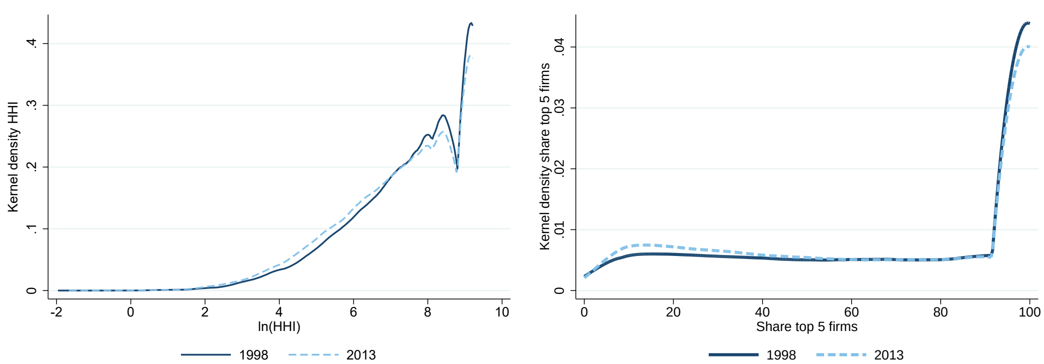


Source: Authors' calculation with data from the 1999, 2004, 2009, and 2014 Economic Censuses, INEGI. Figures are weighted by the labor force.

Figure 2: Labor Market Concentration Distribution

(a) HHI

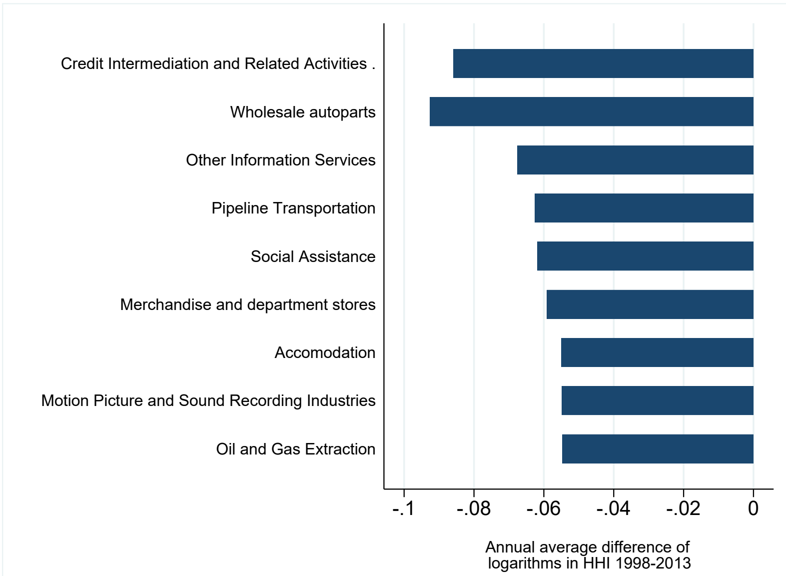
(b) Share top 5 firms (%)



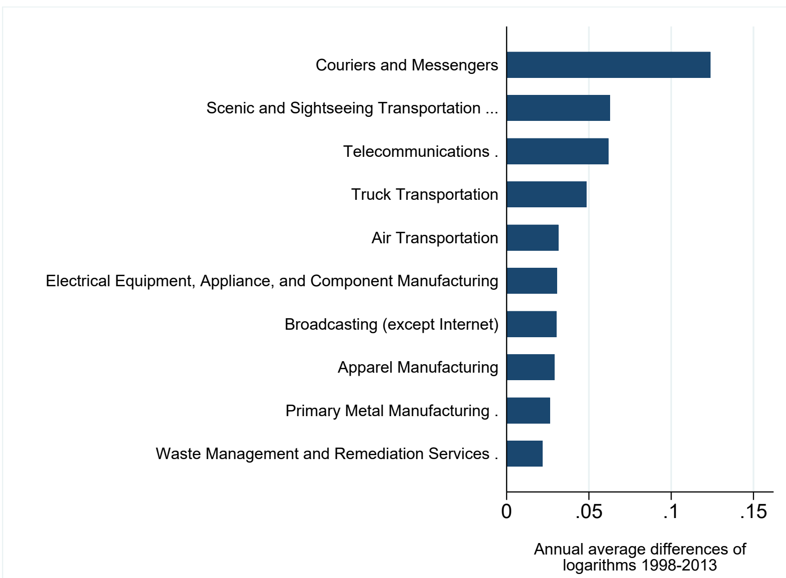
Source: Authors' calculation with data from the 1999, 2004, 2009, and 2014 Economic Censuses, INEGI.

Figure 3: Top Increases and Decreases in Labor Market Concentration

(a) Top 10 sectors reductions in labor market concentration

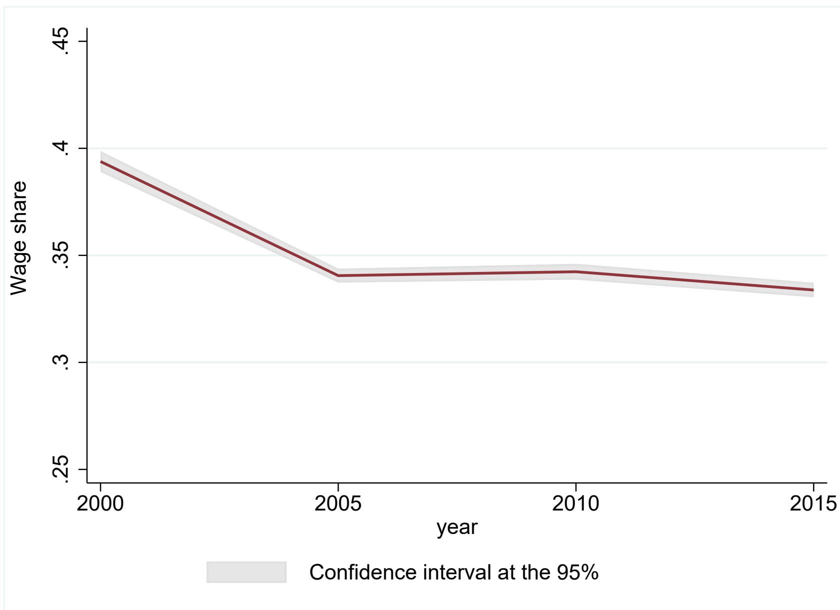


(b) Top 10 sectors increases in labor market concentration



Source: Authors' calculation with data from the 1999 and 2014 Economic Censuses, INEGI. Figures are weighted by the labor force.

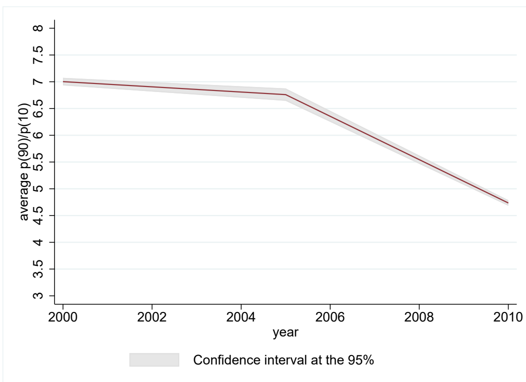
Figure 4: Mean Wage Share



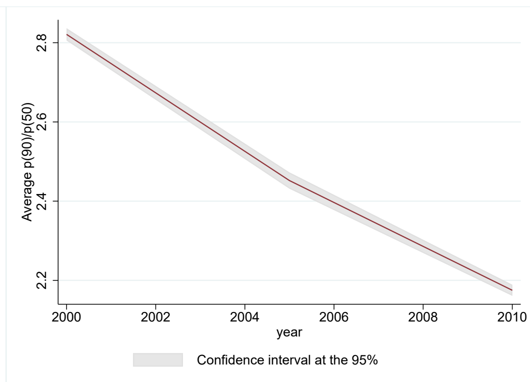
Source: Authors' calculation with data from the 1999, 2004, 2009, and 2014 Economic Censuses, INEGI. Figures are weighted by the labor force.

Figure 5: Evolution of Inequality Indicators

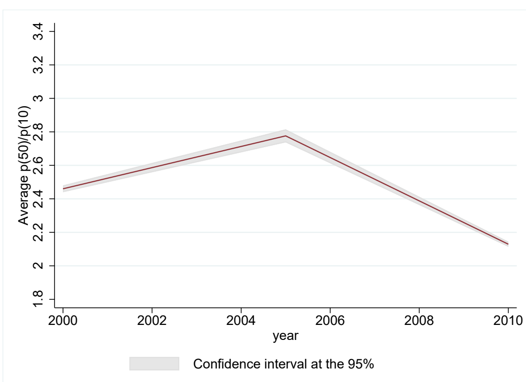
(a) P90/P10



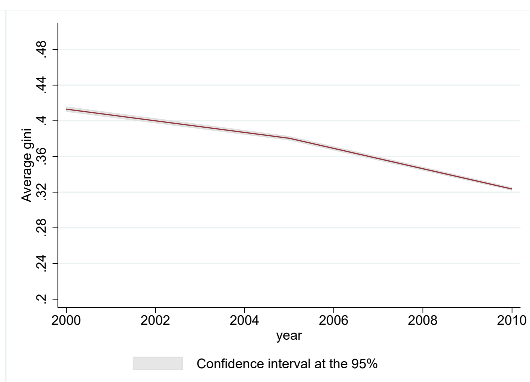
(b) P90/P50



(c) P50/P10



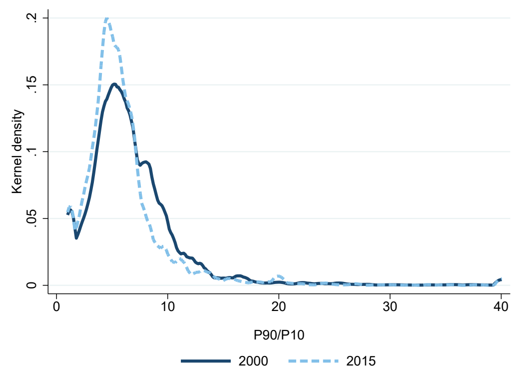
(d) Gini



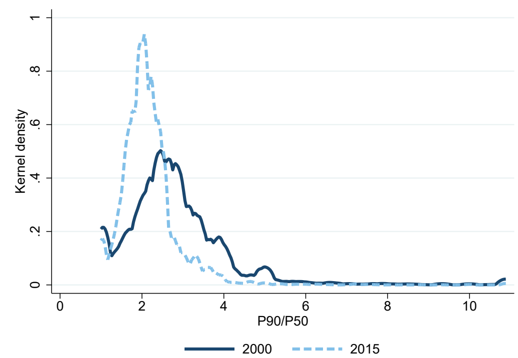
Source: Authors' calculation with data from the 2000 and 2010 Population and Hosuing Censuses, as well as the 2015 Intercensal Survey, INEGI. Figures are weighted by the labor force. All cells (NAICS 3- digits sector-zone) with less than ten observations are not considered in the calculations.

Figure 6: Kernel Densities Inequality Indicators

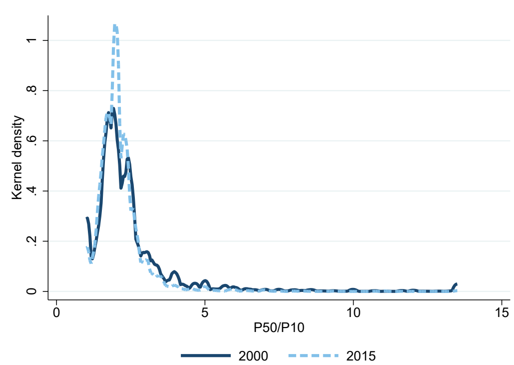
(a) P90/P10



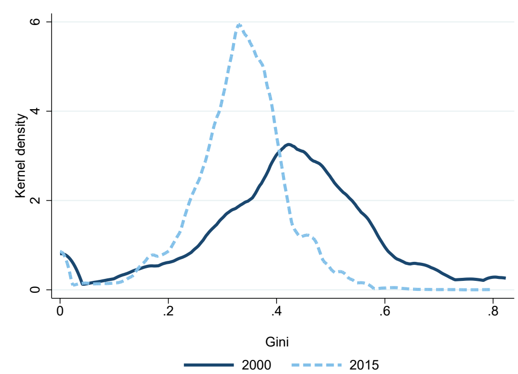
(b) P90/P50



(c) P50/P10



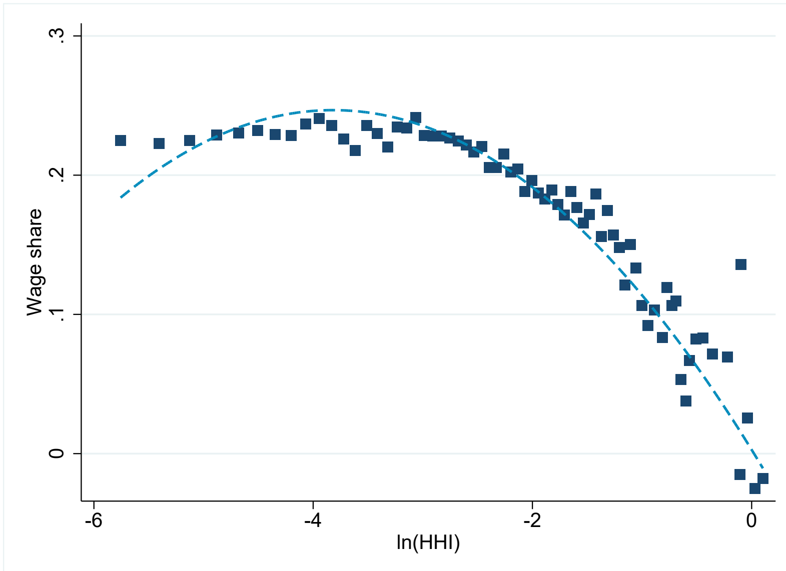
(d) Gini



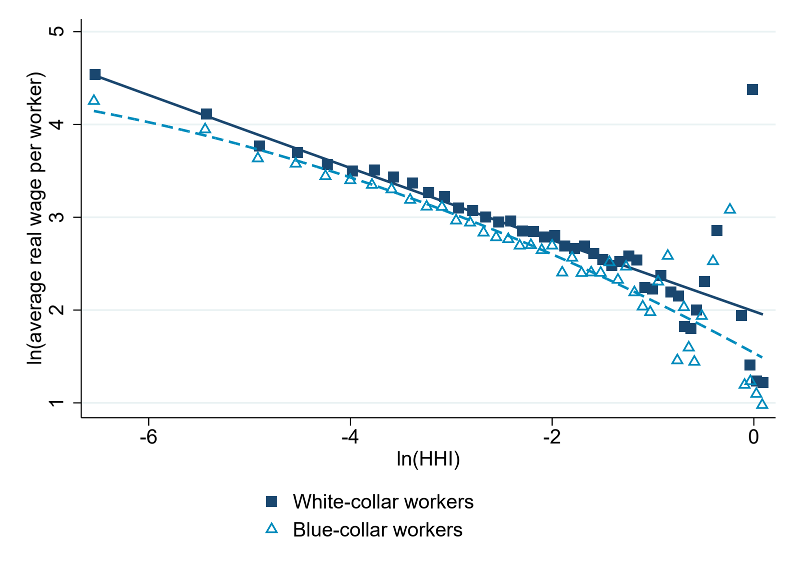
Source: Authors' calculation with data from the 2000 and 2010 Population and Hosuing Censuses, as well as the 2015 Intercensal Survey, INEGI. Figures are weighted by the labor force. All cells (NAICS 3- digits sector-zone) with less than ten observations are not considered in the calculations.

Figure 7: Wage Share, Wages, and Competition

(a) Wage share vs. ln(HHI)



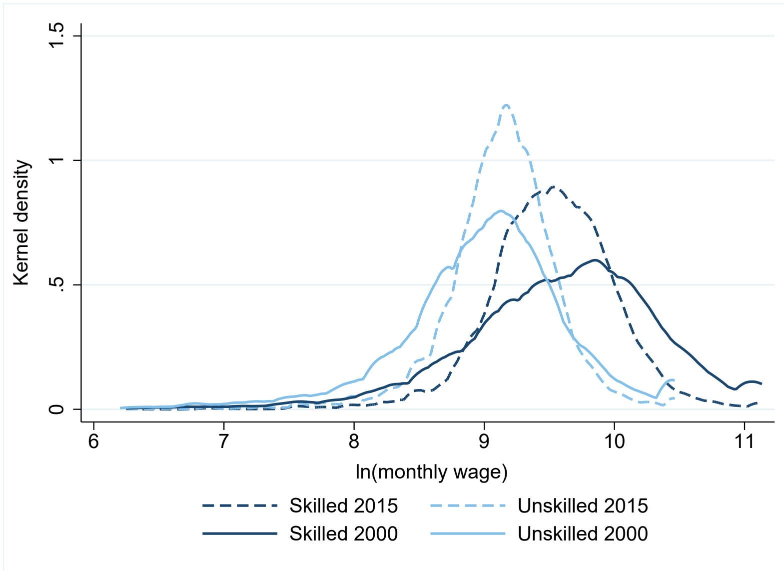
(b) ln(wages) vs. ln(HHI)



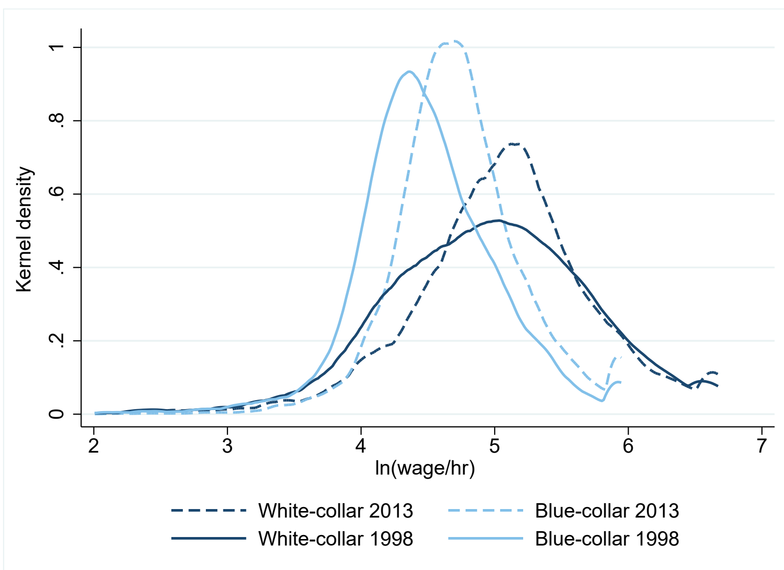
Source: Authors' calculation with data from the 1999, 2009, and 2014 Economic Censuses, as well as the 2000 and 2010 Population and Housing Censuses, and the 2015 Inter-Censal Survey, INEGI.

Figure 8: Evolution of Wages Skilled-Unskilled and White vs. Blue-Collar

(a) Wages skilled vs. unskilled



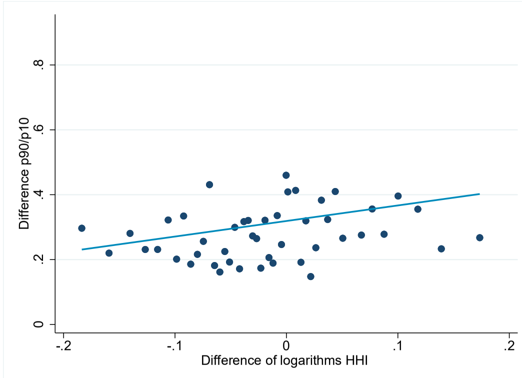
(b) Wages White vs. blue-collar



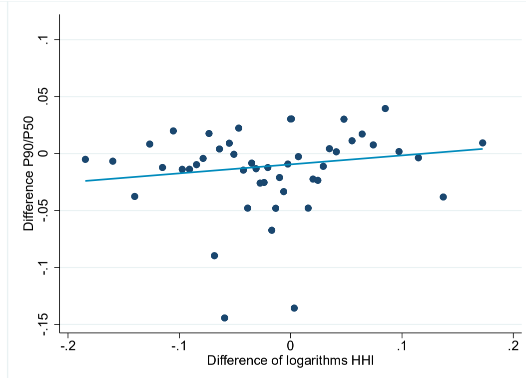
Source: Authors' calculation with data from the 2000 and 2010 Population and Housing Censuses, and the 2015 Inter-Censal Survey, as well as the 2014 and 1999 Economic Censuses.

Figure 9: Inequality Measures vs. Labor Market Concentration

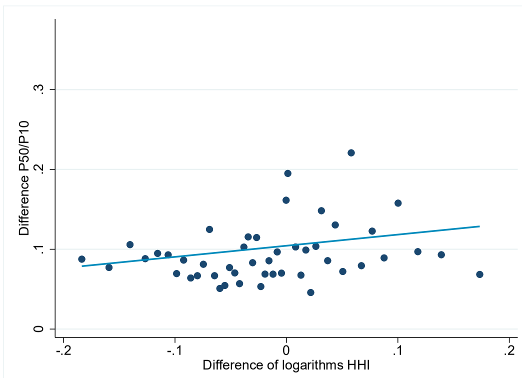
(a) P90/P10 vs. ln(HHI)



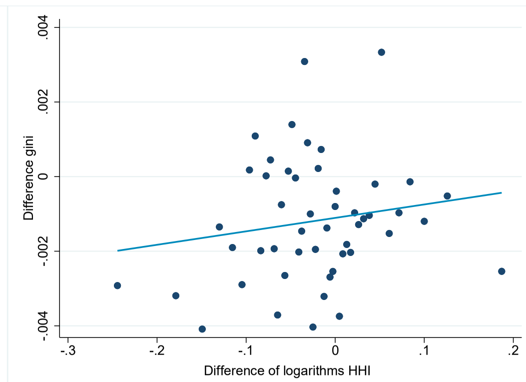
(b) P90/P50 vs. ln(HHI)



(c) P50/P10 vs. ln(HHI)



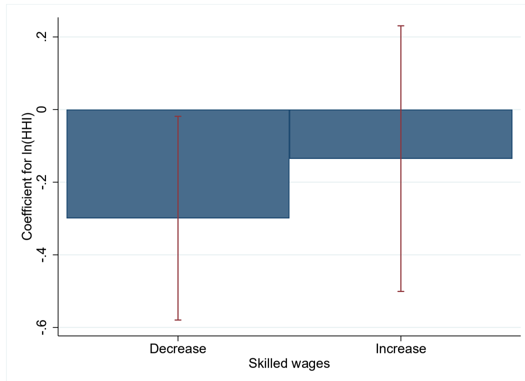
(d) Gini vs. ln(HHI)



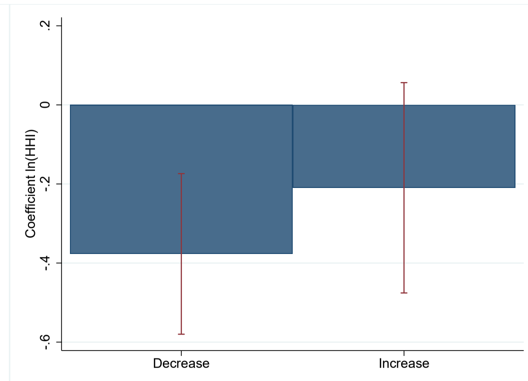
Source: Authors' calculation with data from the 2000 and 2010 Population and Housing Censuses, as well as the 2015 Inter-censal Survey, INEGI. Figures are weighted by the labor force. All cells (NAICS 3-digits sector-zone) with less than ten observations are not considered in the calculations.

Figure 10: Asymmetry of Labor Market Concentration Effects on Labor Outcomes

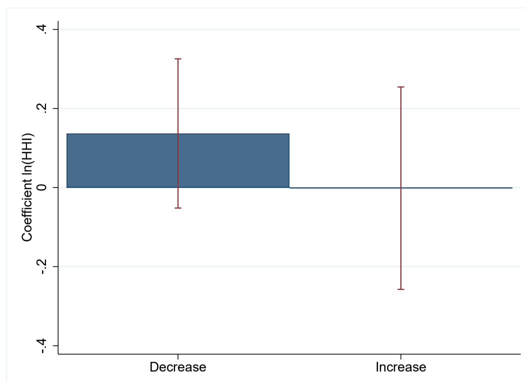
(a) Wages skilled



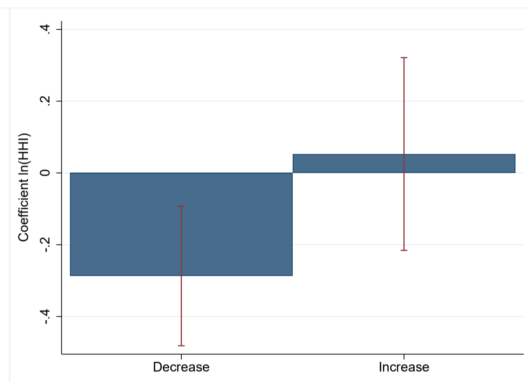
(b) Wages unskilled



(c) Skill premium



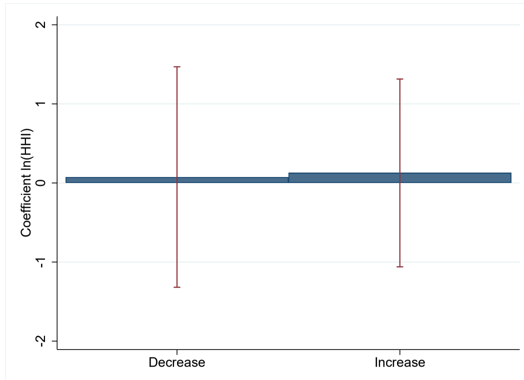
(d) Wage share



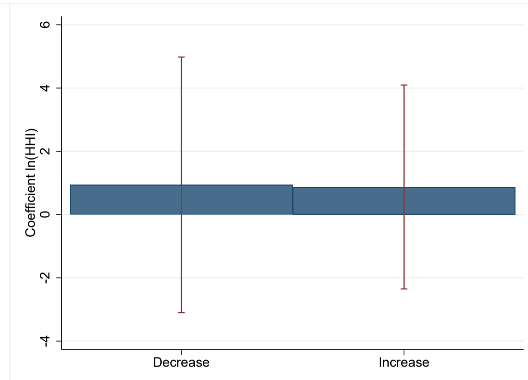
Source: Authors' calculation with data from the 2000 and 2010 Population and Housing Censuses, as well as the 2015 Intercensal Survey, INEGI. Figures are weighted by the labor force. All cells (NAICS 3-digits sector-zone) with less than ten observations are not considered in the calculations.

Figure 10 Asymmetry of Labor Market Concentration Effects on Labor Outcomes: continued

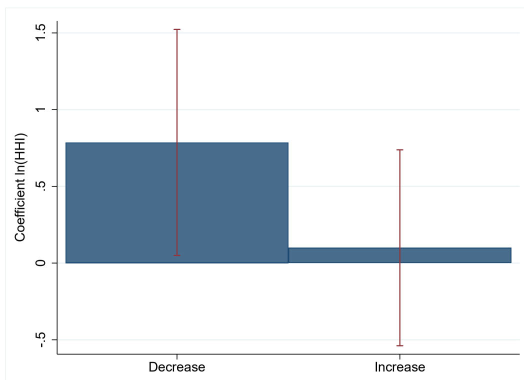
(a) P50/P10



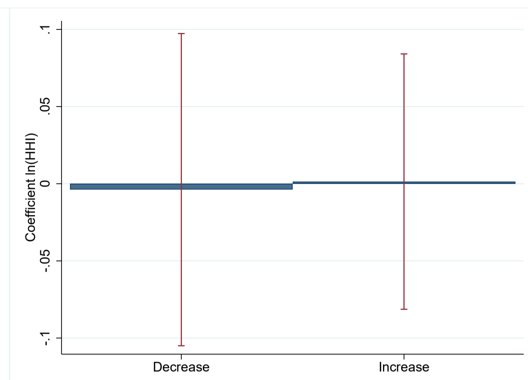
(b) P90/P10



(c) P90/P50



(d) Gini



Source: Authors' calculation with data from the 2000 and 2010 Population and Housing Censuses, as well as the 2015 Inter-censal Survey, INEGI. Figures are weighted by the labor force. All cells (NAICS 3-digits sector-zone) with less than ten observations are not considered in the calculations.

Tables

Table 1: IV estimates of the wage share and wages by skill level over labor market concentration

Dependent variable:	(1) Wage share	(2) ln(wages per worker) blue collar	(3) ln(wages per worker) white collar	(4) Skill premium	(5) Wage share	(6) ln(wages per worker) blue collar	(7) ln(wages per worker) white collar	(8) Skill premium
ln(HHI)	-0.0423***	-0.800***	-0.781***	0.071 ***				
	(0.0141)	(0.0492)	(0.0518)	(0.0172)				
Share top 5					-0.00218***	-0.0413***	-0.0403***	0.0037***
					(0.000730)	(0.00259)	(0.00272)	(0.00089)
Fixed effects market level	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-first stage	3270.706	3270.706	3270.706	3115.27	2344.965	2344.965	2344.965	2737.19
Observations	115,493	115,493	115,493	100,541	115,493	115,493	115,493	100,541

* Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level
Robust standard errors clustered at the market level (NAICS 3-digits code-zone).
*Skill premium is measured as the logarithm of the ratio between white and blue-collar wages.
Source: Authors' calculations using data from the 1999, 2004, 2009, and 2014 Economic censuses.

Table 2: IV estimates of the wage share, wages, and inequality measures over labor market concentration

Dependent variable:	(1) Δ Wage share	(2) Δ ln(average wage skilled)	(3) Δ ln(average wage no skilled)	(4) Skill premium	(5) Δ P90/P10	(6) Δ P90/P50	(7) Δ P50/P10	(8) Δ gini
				Δ ln(HHI)				
Δ ln(HHI)	-0.04701*	-0.120**	-0.137***	0.0366	1.204***	0.135**	0.348***	0.00734
	(0.0301)	(0.0551)	(0.0388)	(0.0393)	(0.379)	(0.0664)	(0.128)	(0.00853)
Δ ln(migration net inlows)	-0.0001868	-0.00519***	-0.00400***	-0.00115***	-0.00306	-0.000411	0.000334	-0.000118
	(0.00023)	(0.000358)	(0.000228)	(0.000230)	(0.00355)	(0.000620)	(0.00120)	(0.0000788)
Δ Informal rate	-0.0012	-0.0543*	-0.109***	0.0245	0.177	-0.0418	0.106	-0.0237***
	(0.01158)	(0.0277)	(0.0206)	(0.0210)	(0.340)	(0.0604)	(0.115)	(0.00793)
Time effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-first stage	1016.882	1016.882	1016.882	712.607	1250.851	1250.851	1250.851	1250.851
				Δ Share top 5				
Δ Share top 5	-0.0024	-0.00652**	-0.00716***	0.00196	0.0674***	0.00776**	0.0193***	0.000372
	(0.0018)	(0.00299)	(0.00204)	(0.00207)	(0.0211)	(0.00366)	(0.00713)	(0.000473)
Δ ln(migration inflows)	-0.00013	-0.00501***	-0.00382***	-0.00122***	-0.00425	-0.000494	-0.0000657	-0.000116
	(0.00024)	(0.000382)	(0.000239)	(0.000251)	(0.00366)	(0.000635)	(0.00124)	(0.0000807)
Δ Informal rate	-0.0013	-0.0569**	-0.110***	0.0250	0.128	-0.0480	0.0937	-0.0236***
	(0.0116)	(0.0279)	(0.0206)	(0.0212)	(0.339)	(0.0603)	(0.115)	(0.00791)
Time effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-first stage	833.341	833.341	833.341	550.298	956.704	956.704	956.704	956.704
Observations	48,820	48,820	48,820	37,046	17,372	17,372	17,372	17,372

* Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level
Robust standard errors clustered at the market level (NAICS 3-digits code-zone).
Source: Authors' calculations using data from the 1999, 2004, 2009, and 2014 Economic censuses, the 2000, and 2010 Population and Housing Census, and the Intercensal Survey 2015.
*Observations in columns (5) to (8) are lower as cells (combinations of NAICS sectors and zones) are too small in size.

Table 3: IV estimates of the wage share, wages, and inequality measures over labor market concentration: incumbents

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:	Δ ln(average wage skilled)	Δ ln(average wage no skilled)	Skill premium	Δ P90/P10	Δ P90/P50	Δ P50/P10	Δ gini
Δ ln(HHI)							
Δ ln(HHI)	-0.203***	-0.213***	0.0381	0.111	0.175*	0.120	0.00372
	(0.0704)	(0.0491)	(0.0390)	(0.385)	(0.103)	(0.136)	(0.00840)
Δ ln(migration inflows)	-0.00639***	-0.00507***	-0.000818***	-0.00673*	-0.00272***	-0.000674	-0.0000896
	(0.000453)	(0.000291)	(0.000234)	(0.00371)	(0.000767)	(0.00131)	(0.0000773)
Δ Informal rate	-0.0285	-0.124***	0.0403	-0.0494	0.0152	-0.176	-0.0145*
	(0.0496)	(0.0388)	(0.0261)	(0.356)	(0.0476)	(0.126)	(0.00776)
Time effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-first stage	1161.528	1161.528	828.965	576.366	576.366	769.248	576.366
Δ Share top 5							
Δ Share top 5	-0.0109***	-0.0111***	0.00202	0.00653	0.00965*	0.00642	0.000207
	(0.00377)	(0.00257)	(0.00203)	(0.0207)	(0.00570)	(0.00730)	(0.000465)
Δ ln(migration inflows)	-0.00605***	-0.00477***	-0.000890***	-0.00684*	-0.00289***	-0.000832	-0.0000982
	(0.000491)	(0.000311)	(0.000259)	(0.00378)	(0.000779)	(0.00134)	(0.0000792)
Δ Informal rate	-0.0317	-0.126***	0.0404	-0.0539	0.0186	-0.178	-0.0146*
	(0.0497)	(0.0388)	(0.0261)	(0.355)	(0.0479)	(0.125)	(0.00773)
Time effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-first stage	819.831	819.831	601.135	463.741	463.741	463.741	463.741
Observations	48,820	48,820	37,821	17,372	17,372	17,372	17,372

* Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level
Robust standard errors clustered at the market level (NAICS 3-digits code-zone).
Source: Authors' calculations using data from the 1999, 2009, and 2014 Economic censuses, the 2000, and 2010 Population and Housing Census, and the Intercensal Survey 2015.
*Observations in columns (4) to (7) are lower as cells (combinations of NAICS sectors and zones) are too small in size.

Table 4: IV estimates of the wage share, wages, and inequality measures over labor market concentration by sector

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	Δ Wage share	Δ ln(average wage skilled)	Δ ln(average wage no skilled)	Skill premium	Δ P90/P10	Δ P90/P50	Δ P50/P10	Δ gini
				Manufacturing				
Δ ln(HHI)	0.1007	-0.0986	-0.456***	0.1926*	5.372***	0.282	2.197***	0.00422
	(0.1006)	(0.320)	(0.173)	(0.1072)	(1.789)	(0.348)	(0.651)	(0.0447)
Δ ln(migration inflows)	0.0006	-0.00743***	-0.00361***	-0.00245***	0.00717	0.00341**	-0.00138	0.000163
	(0.0003)	(0.00111)	(0.000572)	(0.00059)	(0.00853)	(0.00161)	(0.00310)	(0.000208)
Δ Informal rate	-0.004	-0.157*	-0.148***	0.02719	-0.0792	0.00880	0.0883	-0.0553***
	(0.0179)	(0.0816)	(0.0486)	(0 .0489)	(0.799)	(0.134)	(0.291)	(0.0190)
Time effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-first stage	45.226	45.226	45.226	36.94	48.932	48.932	48.932	48.932
Observations	12,351	12,351	12,351	10,465	4,479	4,479	4,479	4,479
				Services				
Δ ln(HHI)	-0.0456	-0.155***	-0.152***	0.0297	0.469	0.0436	0.179	0.00295
	(0.0398)	(0.0587)	(0.0435)	(0.0432)	(0.440)	(0.0738)	(0.148)	(0.00955)
Δ ln(migration inflows)	-0.000241	-0.00444***	-0.00372***	-0.000856***	-0.0126***	-0.000981	-0.00237	-0.000158
	(0.000295)	(0.000422)	(0.000291)	(0.000283)	(0.00453)	(0.000758)	(0.00153)	(0.0000971)
Δ Informal rate	0.0111	-0.0245	-0.131***	0.0545**	0.734*	-0.0646	0.315**	-0.0148
	(0.0151)	(0.0320)	(0.0248)	(0.0252)	(0.424)	(0.0733)	(0.143)	(0.00960)
Time effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-first stage	998.479	998.479	998.479	712.607	966.036	966.036	966.036	966.036
Observations	32,806	32,806	32,806	24,581	11,650	11,650	11,650	11,650

* Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level
Robust standard errors clustered at the market level (NAICS 3-digits code-zone).
Source: Authors' calculations using data from the 1999, 2009, and 2014 Economic censuses, the 2000, and 2010 Population and Housing Census, and the Intercensal Survey 2015.
*Observations in columns (5) to (8) are lower as cells (combinations of NAICS sectors and zones) are too small in size.

Table 5: IV estimates of the wage share, wages, and inequality measures over labor market concentration: unionization

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	Δ Wage share	Δ ln(average wage skilled)	Δ ln(average wage no skilled)	Skill premium	Δ P90/P10	Δ P90/P50	Δ P50/P10	Δ gini
				Lowly-unionized				
Δ ln(HHI)	-0.119**	-0.187*	-0.248***	0.0445	1.449**	-0.0362	0.613***	0.00981
	(0.0479)	(0.0963)	(0.0626)	(0.0654)	(0.568)	(0.0988)	(0.190)	(0.0127)
Δ ln(migration inflows)	0.0008***	-0.00647***	-0.00410***	-0.00161***	0.00541	0.00203**	0.00250	-0.000235**
	(0.0002)	(0.000499)	(0.000293)	(0.000293)	(0.00472)	(0.000822)	(0.00158)	(0.000105)
Δ Informal rate	-0.00501	-0.0528	-0.0838***	0.00905	1.008**	-0.154*	0.407***	-0.0176
	(0.0129)	(0.0416)	(0.0286)	(0.0281)	(0.442)	(0.0804)	(0.148)	(0.0107)
Time effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-first stage	376.717	376.717	376.717	260.881	502	502	502	502
Observations	34,144	34,144	34,144	24,584	11,229	11,229	11,229	11,229
				Highly-unionized				
Δ ln(HHI)	0.0364	-0.0154	0.0195	0.0211	1.031**	0.261***	0.153	0.00704
	(0.0485)	(0.0488)	(0.0427)	(0.0381)	(0.519)	(0.0917)	(0.179)	(0.0118)
Δ ln(migration inflows)	-0.0019***	-0.00366***	-0.00390***	-0.000463	-0.00783	-0.00252**	-0.000817	-0.0000377
	(0.0005)	(0.000510)	(0.000386)	(0.000385)	(0.00569)	(0.00100)	(0.00197)	(0.000127)
Δ Informal rate	0.0053	-0.0773**	-0.154***	0.0454	-0.253	0.0848	-0.0614	-0.0270**
	-0.023	(0.0354)	(0.0297)	(0.0305)	(0.535)	(0.0941)	(0.185)	(0.0122)
Time effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-first stage	877.845	877.845	877.845	260.881	766.57	766.57	766.57	766.57
Observations	14,676	14,676	14,676	13,237	6,496	6,496	6,496	6,496

* Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level
Robust standard errors clustered at the market level (NAICS 3-digits code-zone).
Source: Authors' calculations using data from the 1999, 2009, and 2014 Economic censuses, the 2000, and 2010 Population and Housing Census, and the Intercensal Survey 2015.
*Observations in columns (5) to (8) are lower as cells (combinations of NAICS sectors and zones) are too small in size.

Table 6: IV estimates of the wage share, wages, and inequality measures over labor market concentration: interaction with informality

Dependent variable:	(1) Δ Wage share	(2) Δ ln(average wage skilled)	(3) Δ ln(average wage no skilled)	(4) Skill premium	(5) Δ P90/P10	(6) Δ P90/P50	(7) Δ P50/P10	(8) Δ gini
				Δ ln(HHI)				
Δ ln(HHI)	-0.0588	-0.119**	-0.118***	0.0327	1.275***	0.127*	0.390***	0.00701
	(0.0359)	(0.0572)	(0.0400)	(0.0397)	(0.382)	(0.0665)	(0.130)	(0.00855)
Δ ln(HHI)*Δ Informal rate	-0.0289**	0.0139	0.0473***	-0.0101	0.182	-0.0270	0.107**	-0.00105
	(0.0120)	(0.0193)	(0.0174)	(0.0137)	(0.153)	(0.0253)	(0.0519)	(0.00323)
Δ ln(migration inflows)	-0.000175	-0.00520***	-0.00402***	-0.00115***	-0.00363	-0.000348	-0.000000177	-0.000116
	(0.000230)	(0.000358)	(0.000232)	(0.000231)	(0.00359)	(0.000622)	(0.00122)	(0.0000791)
Δ Informal rate	-0.0622**	-0.0239	-0.00593	0.00353	0.379	-0.0743	0.225*	-0.0249***
	(0.0279)	(0.0514)	(0.0456)	(0.0355)	(0.379)	(0.0675)	(0.129)	(0.00879)
Time effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-first stage	303.914	303.914	303.914	280.534	301.67	301.67	301.67	301.67
				Δ Share top 5				
Δ Share top 5	-0.00303	-0.00623**	-0.00570***	0.00171	0.0756***	0.00718*	0.0237***	0.000353
	(0.00185)	(0.00305)	(0.00216)	(0.00211)	(0.0222)	(0.00371)	(0.00754)	(0.000480)
Δ Share top 5*Δ Informal rate	-0.00140**	0.000740	0.00275**	-0.000556	0.0138	-0.00144	0.00740**	-0.0000453
	(0.000580)	(0.00103)	(0.00108)	(0.000758)	(0.00981)	(0.00152)	(0.00334)	(0.000194)
Δ ln(migration inflows)	-0.0000903	-0.00505***	-0.00391***	-0.00119***	-0.00497	-0.000431	-0.000451	-0.000113
	(0.000241)	(0.000388)	(0.000247)	(0.000254)	(0.00372)	(0.000639)	(0.00126)	(0.0000812)
Δ Informal rate	-0.0623**	-0.0215	0.0175	-0.00151	0.394	-0.0811	0.237*	-0.0247***
	(0.0279)	(0.0576)	(0.0568)	(0.0421)	(0.390)	(0.0697)	(0.133)	(0.00911)
Time effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-first stage	819.831	819.831	601.135	463.741	269.317	269.317	269.317	269.317
Observations	48,820	48,820	37,821	17,372	17,372	17,372	17,372	17,372

* Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level
Robust standard errors clustered at the market level (NAICS 3-digits code-zone).
Source: Authors' calculations using data from the 1999, 2009, and 2014 Economic censuses, the 2000, and 2010 Population and Housing Census, and the Intercensal Survey 2015.
*Observations in columns (4) to (8) are lower as cells (combinations of NAICS sectors and zones) are too small in size.

Table 7: Estimates of the wage share, wages, and inequality measures over the number of entrants

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	Δ Wage share	Δ ln(average wage skilled)	Δ ln(average wage no skilled)	Skill premium	Δ P90/P10	Δ P90/P50	Δ P50/P10	Δ gini
Dummy large entrants	0.000133	0.00561***	-0.00638	0.0111***	0.111***	0.0134***	0.0329***	0.000885**
	(0.000879)	(0.00152)	(0.00684)	(0.0009)	(0.0173)	(0.00311)	(0.00587)	(0.000402)
Δ ln(migration inflows)	-0.000640***	-0.00324***	-0.00103	-0.00213	-0.00700**	-0.000324	-0.00137	-0.000123
	(0.000182)	(0.000313)	(0.00116)	(0.00133)	(0.00353)	(0.000636)	(0.00120)	(0.0000823)
Δ Informal rate	0.0305**	-0.0746***	0.0209	-0.168	-0.107	0.00214	0.00760	-0.0174**
	(0.0155)	(0.0281)	(0.102)	(0.137)	(0.309)	(0.0555)	(0.105)	(0.00734)
Time effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	48,820	48,820	48,820		17,372	17,372	17,372	17,372
Number of large entrants	-0.000712	0.000211**	0.000102	0.000109*	0.00171***	0.000445***	0.000329	0.0000689***
	(0.00467)	(0.0000890)	(0.0000626)	(0.0000610)	(0.000626)	(0.000122)	(0.000212)	(0.0000158)
Δ ln(migration inflows)	0.0168	-0.00316***	-0.00140*	-0.00158	-0.00159	0.0000325	0.000527	-0.000157**
	(0.0225)	(0.000736)	(0.000850)	(0.000992)	(0.00345)	(0.000618)	(0.00117)	(0.0000799)
Δ Informal rate	2.600	-0.0910	0.0325	-0.183	-0.214	-0.00887	-0.0255	-0.0179**
	(1.970)	(0.101)	(0.106)	(0.151)	(0.309)	(0.0554)	(0.105)	(0.00733)
Time effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	48,820	48,820	48,820	40713	17,372	17,372	17,372	17,372

* Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level
Robust standard errors clustered at the market level (NAICS 3-digits code-zone).
Source: Authors' calculations using data from the 1999, 2009, and 2014 Economic censuses, the 2000, and 2010 Population and Housing Census, and the Intercensal Survey 2015.
*Observations in columns (5) to (8) are lower as cells (combinations of NAICS sectors and zones) are too small in size.

Online Appendix

A Construction of Local Labor Markets

We use 3-digit NAICS codes available in both the Economic Censuses and the Population and Housing Censuses to define industries.

To define the geographic extension of the labor market, we use the commuting zones calculated by Blyde et al. (2020). They start with the 59 metropolitan statistical areas defined by CONAPO, each of which includes a group of municipalities showing a high degree of socioeconomic interactions. To create additional commuting zones to cover the entire country, they develop an algorithm to first, identify central municipalities and, second, to assign peripheral municipalities to central municipalities using a set of criteria. To identify central municipalities, they develop an index of urbanity at the municipality level, combining the standardized values of Population, percent of urban Population, urban density, percent of Population working in non-primary activities, and number of municipalities from which people come to work. A municipality is defined as central if its urban index score is above the 25th percentile. To assign peripheral municipalities to a central one, they followed three criteria: i) proximity: the peripheral municipality is less than 100 km from the central one; ii) commuting: at least one person from the peripheral municipality is working in the central municipality; and iii) positive correlation in the urban employment rates between peripheral and central municipalities. Assignment of peripheral municipalities followed an iterative process. Most municipalities were assigned through this process; a small number of municipalities were assigned by relaxing criterion iii); finally, a small number of small and rural municipalities were not assigned to any central municipality and were treated as independent commuting zones.

The results of this process lead to 780 zones, which are shown in the map of Figure E2.

B Database Construction and Variables Definition

To construct our database, we merge information from the Economic Censuses and the Population and Housing Censuses, along with the 2015 Inter-censal Survey. It is important to note that these statistical projects occur at different points in time. Therefore, as shown in Figure E3, we match the 1999 Economic Census, which obtained information from 1998, with the 2000 Population and Housing Census. Similarly, we merge data from the 2009 Economic Census with the 2010 Population and Housing Census, and so on.

The main variables of analysis are constructed as follows:

Wage Share: Following Ibarra and Ros (2019) we analyze the wage share as total remunerations over value-added obtained from the Economic Censuses. Different from these authors, we do not make any adjustments to construct a Labor Income Share based on this variable.

White and blue-collar wages: We use the variables from the Economic Census that account for remunerations of these types of workers, along with the total number of hours workers. Therefore, these variables are defined as hourly wages.

Skilled and unskilled wages: We construct these variables using data from the Population and Housing Censuses on monthly wages and educational attainment. As previously mentioned, we defined skilled as those workers with high school or more. We also have an alternative definition that calculates hourly wages, but this variable is only available for the 2000 and 2010 Population and Housing Censuses. We use this for robustness purposes in Table F6.

P90/P10: For each labor market (defined as NAICS 3-digits sector-zone), we calculate the ratio of the 90$^{\text{th}}$ percentile over the 10$^{\text{th}}$ percentile of wages.

P90/P50: For each labor market (defined as NAICS 3-digits sector- zone), we calculate the ratio of the 90$^{\text{th}}$ percentile over the 50$^{\text{th}}$ percentile of wages.

P50/P10: For each labor market (defined as NAICS 3-digits sector- zone), we calculate the ratio of the 90$^{\text{th}}$ percentile over the 10$^{\text{th}}$ percentile of wages.

Gini coefficient: We calculated the Gini coefficient within each labor market.

Internal migration: We calculate net inflows (inflows vs. outflows) at the labor market level, based on a variable included in the Population and Housing Censuses that indicates whether the individual lived in the same municipality five years ago.

Informality rate: We use a variable included in the Population and Housing Censuses that analyzes whether workers have access to medical services and social security to classify them as formal and informal. Additional variables:

Percentage employed in manufacturing: Percentage of employed people who works in the manufacturing sector at the zone level, obtained from the Population and Housing Censuses.

Population: Number of people living in the zone, obtained from the Population and Housing Censuses.

% ***of population with higher education:*** Percentage of people between 25 and 65 years who have 12 or more years of schooling in the zone, obtained from the Population and Housing Censuses.

Distance from national capital (km): Average distance from the centroid of each municipality in the zone to the center of the capital state (Coyoacan, CDMX).

Distance from regional capital (km): Average Distance from the municipality seats of the zone to the closest urban center of 50 thousand inhabitants or more.

% ***of households with access to water:*** Percentage of households with piped water in the zone.

Technical school, junior college: Number of technical schools or junior colleges in the zone.

Financial services in the zone: Number of commercial and development bank branches in the zone. SIMBAD, INEGI.

Transport infrastructure: Kilometers of interstate road in each zone. SIMBAD, INEGI.

C Geographic Analysis

To give further details on the characteristics of labor market concentration and the labor markets at the regional level, we analyze averages at the zone level.

In Figure E4, we observe labor market concentration for 2013. As the figure shows, a higher level of concentration (higher HHI) is observed in the Northern region of the country, especially near the US border. On the other hand, there are few zones with high labor market concentration in the South, and a few in the South-East. The results are similar when we analyze the share of the top 5 firms in the labor market (panel b of Figure E4).

Analyzing skilled wages in panel (a) of Figure E5, high levels are observed in the North and Central-North, while in some small zones of the Central and the Central-South regions, we also observe high wages. It is worth highlighting that Chiapas and Oaxaca, which are among the country's poorest states, have very few zones with high wages. For unskilled workers (panel b), the pattern does not differ substantially as in the Central-North region and in states like Sonora and Jalisco near the Pacific coast, high wages are observed and, once again, just a handful of high-wages zones in Chiapas and Oaxaca. There is no clear geographical pattern for the change in wages of skilled workers during the period of analysis, as shown in panel C. In contrast, for unskilled workers, there is a zone in the North that exhibits an average increase in wages during this period. This zone is near an industrial corridor related to the automotive industry that has been experiencing important growth in recent years.

Considering inequality measures in Figure E6, we observed that high-inequality labor markets are widespread geographically, at least when we consider the top of the distribution (panels a and b). On the other hand, at the lower level of the distribution (differences between the 10^{th} and the 50^{th} percentiles), there is high inequality in the Central and Central-South Regions.

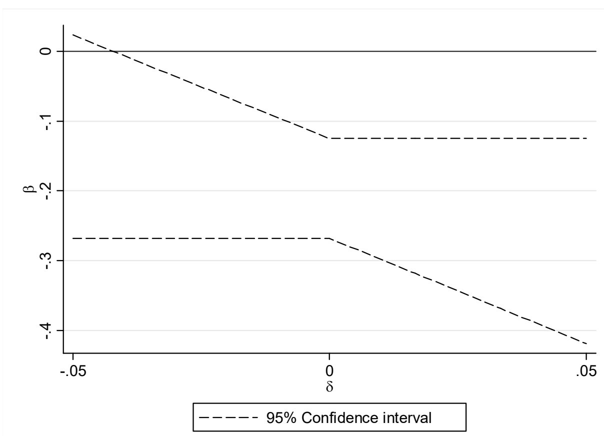
D Plausibly Exogenous Estimates

Following Azar et al. (2022), and using the methodology developed by Conley et al. (2012), we implement a plausibly exogenous instrumental variable strategy. We set the range for the coefficient by including the instrument directly instead of the labor market concentration measure in the second stage of the instrumental variable estimation. If the instrument is fully exogenous, its coefficient in this second stage should be zero (in our case, the upper bound). To define the lower bound, we take the estimated coefficient of the instrument in this second stage.

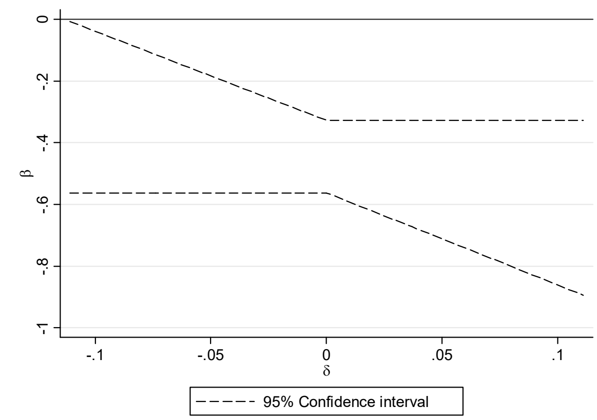
To implement this, we use the Stata command plausexog, developed by Clarke and Matta (2018). As shown in the following graphs, even allowing for some endogeneity of our instrument, the results do not change.

Figure D1: Plausibly Exogenous Estimates

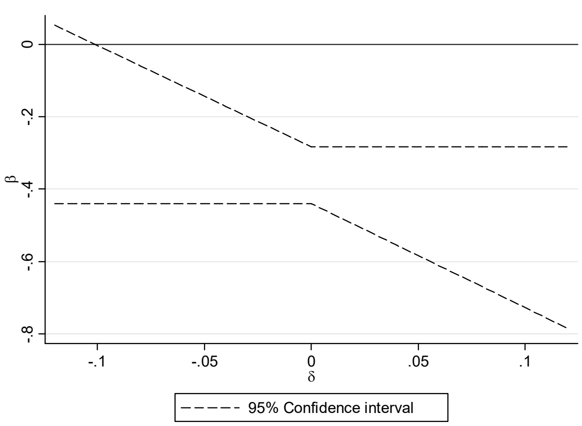
(a) Wage share



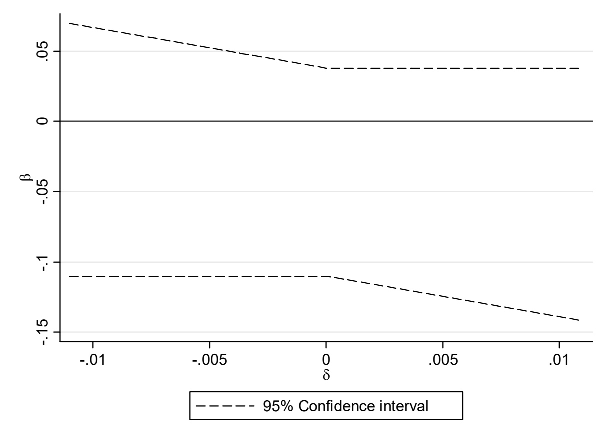
(b) Skilled wages



(c) Unskilled wages



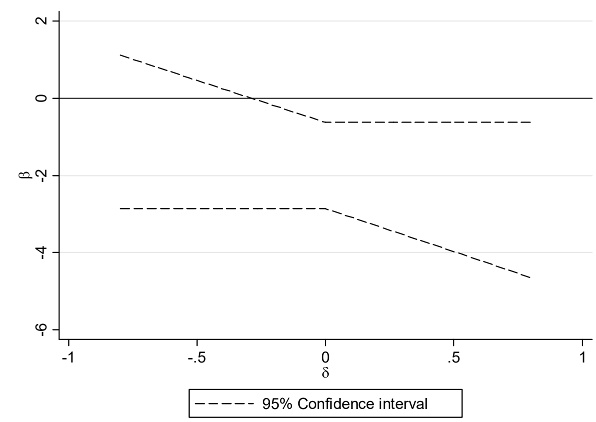
(d) Skill premium



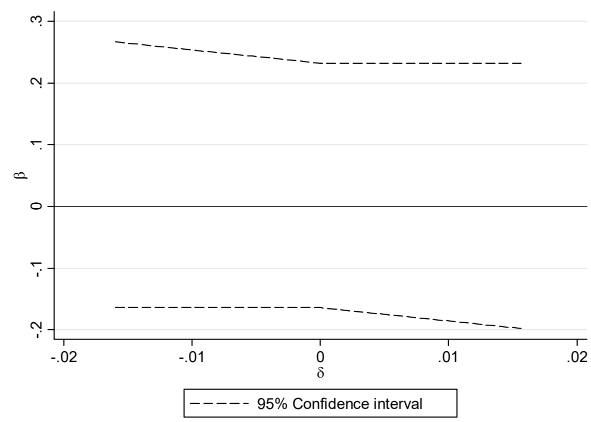
Source: Authors' calculations using data from the 1999, 2009, and 2014 Economic censuses, the 2000 and 2010 Population and Housing Census, and the Intercensal Survey 2015.

Figure D1 Plausibly Exogenous Estimates: continued

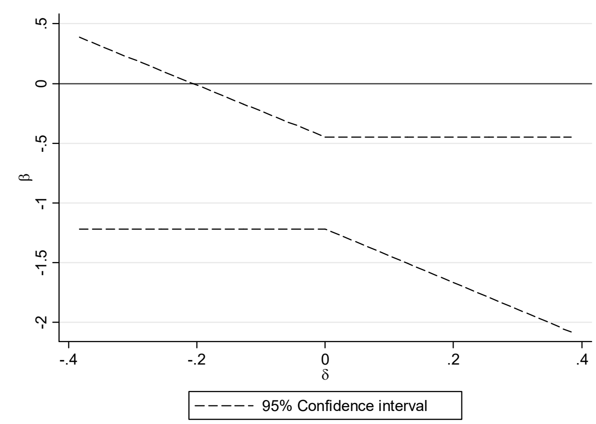
(a) P90/P10



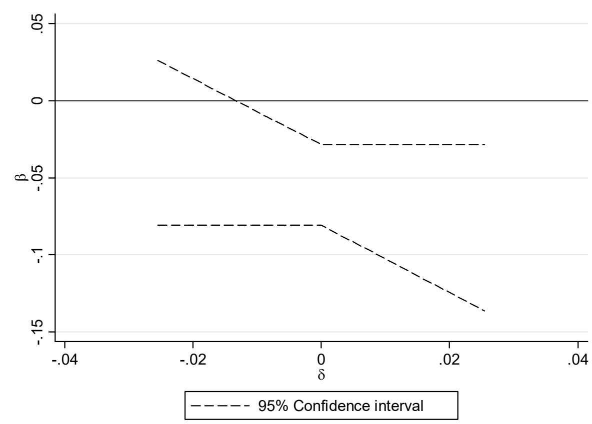
(b) P90/P50



(c) P50/P10



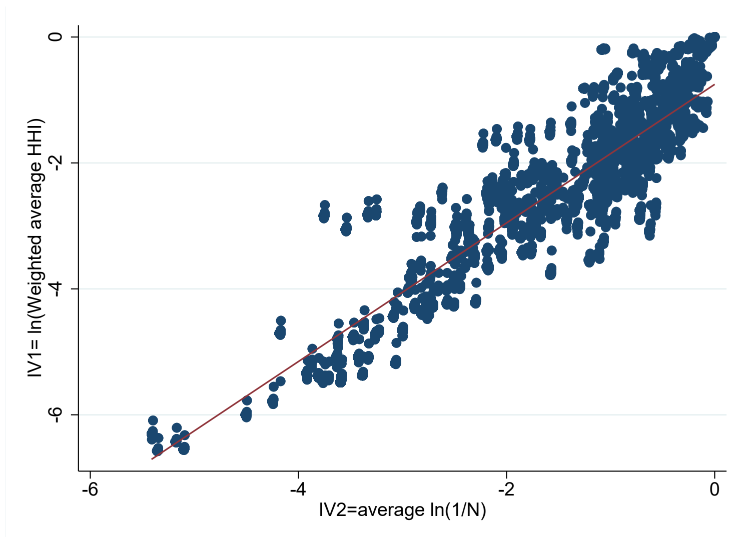
(d) Gini index



Source: Authors' calculations using data from the 1999, 2009, and 2014 Economic censuses, the 2000 and 2010 Population and Housing Census, and the Inter-censal Survey 2015.

E Additional Figures

Figure E1: Correlation Instrumental Variables

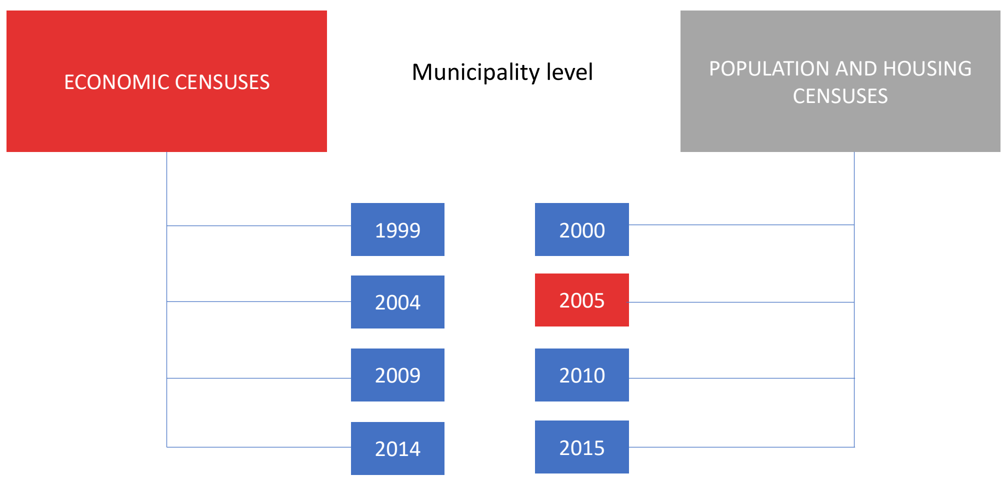


Source: Authors' calculation with data from the 1999, 2004, 2009, and 2014 Economic Censuses, INEGI.

Figure E2: Zones Definition

Source: Blyde et al. (2020)

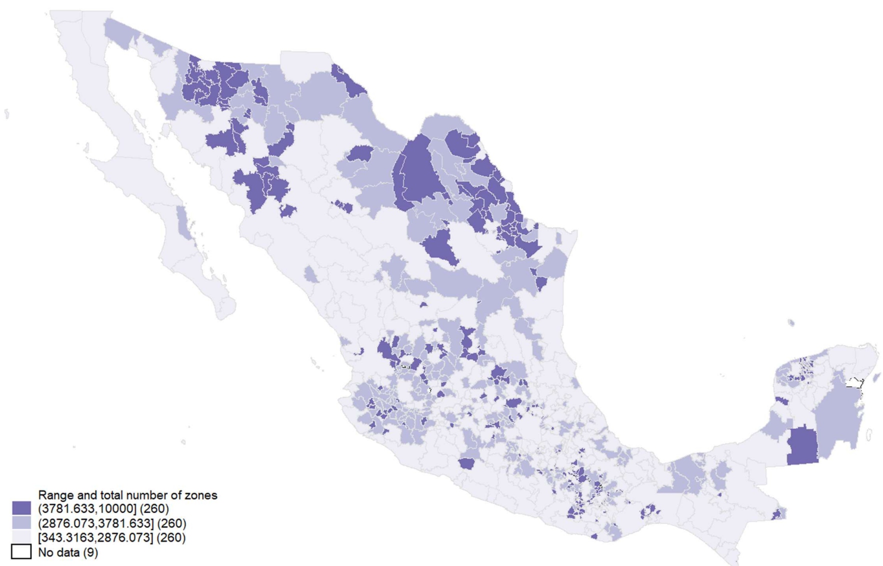
Figure E3: Data Sources and Use



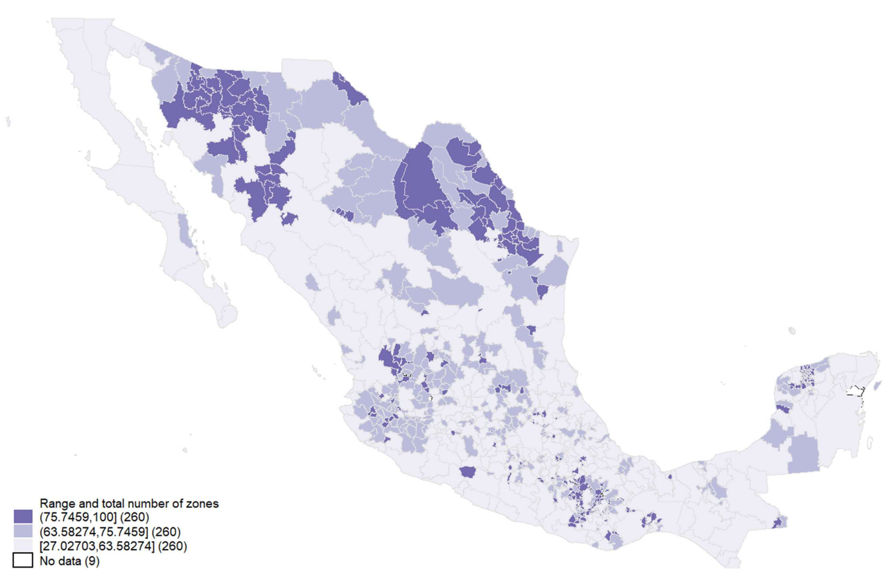
Source: Authors' compilation.

Figure E4: Labor Market Concentration Measures

(a) HHI 2013



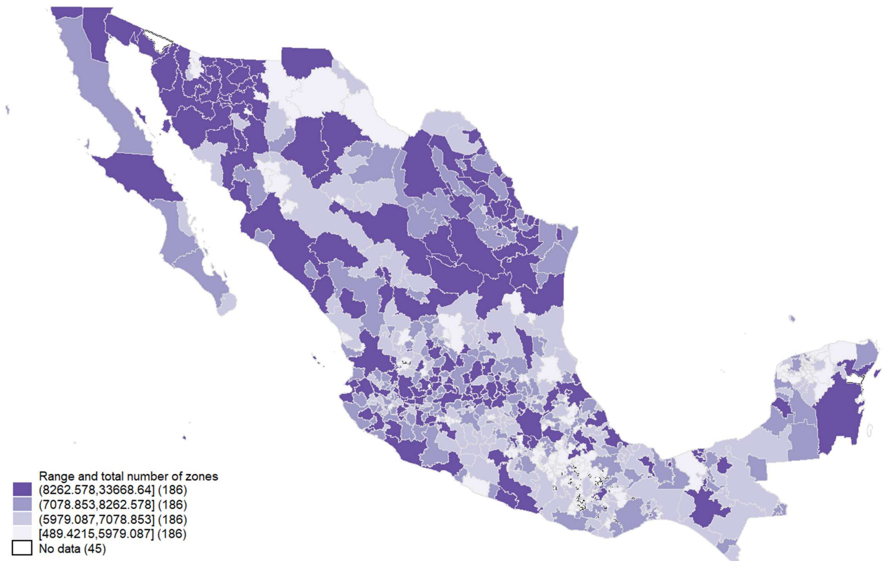
(b) Share top 5 firms (%) 2013



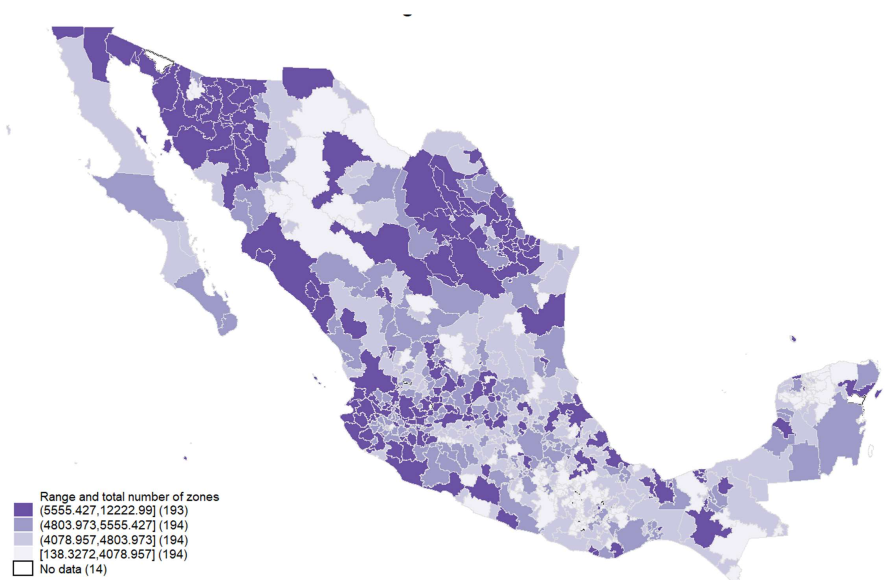
Source: Authors' calculations using data from the 2014 Economic Census, INEGI.

Figure E5: Mean Wages Skilled and Unskilled

(a) Mean wage skilled 2015



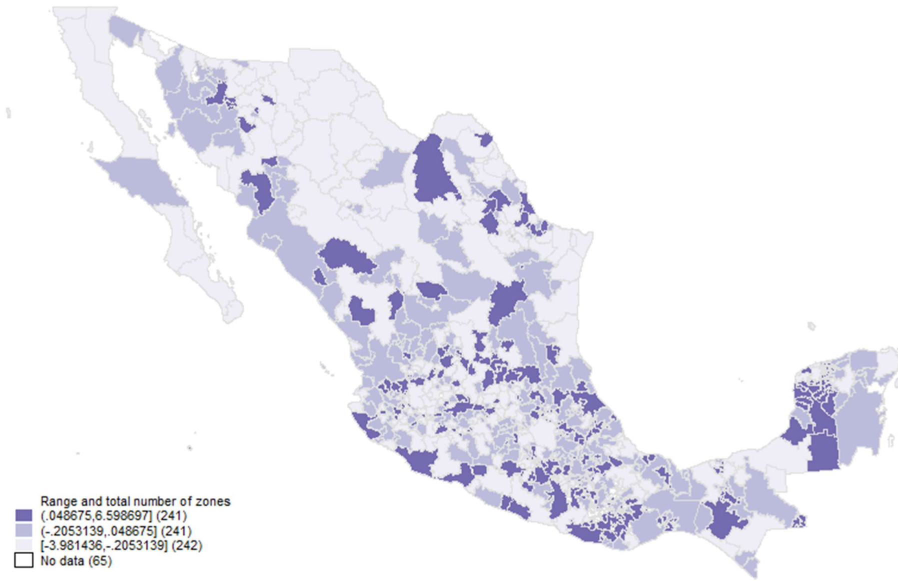
(b) Mean wage unskilled 2015



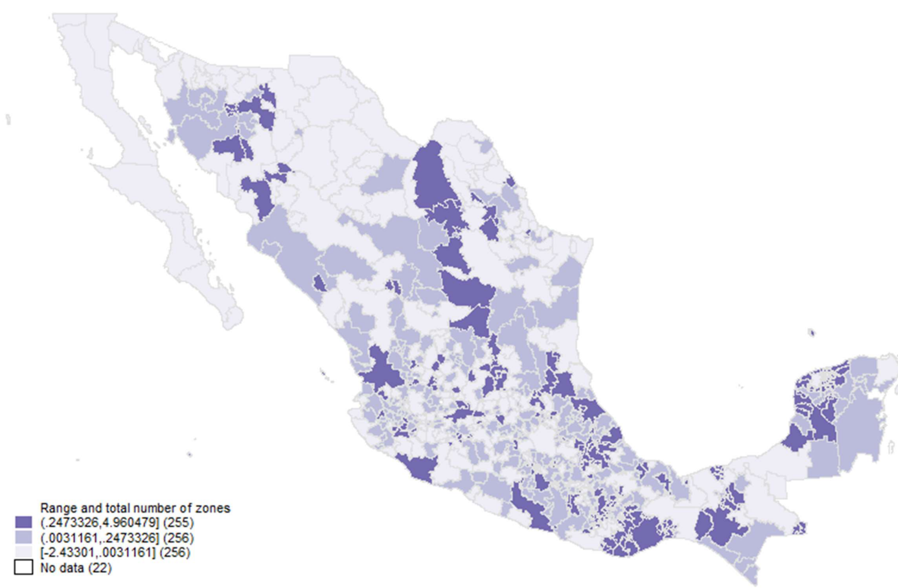
Source: Authors' calculations using data from the 2015 Inter-Censal Survey, INEGI.

Figure E5 Mean Wages Skilled and Unskilled: continued

(a) Changes in mean wages skilled 2000-2015



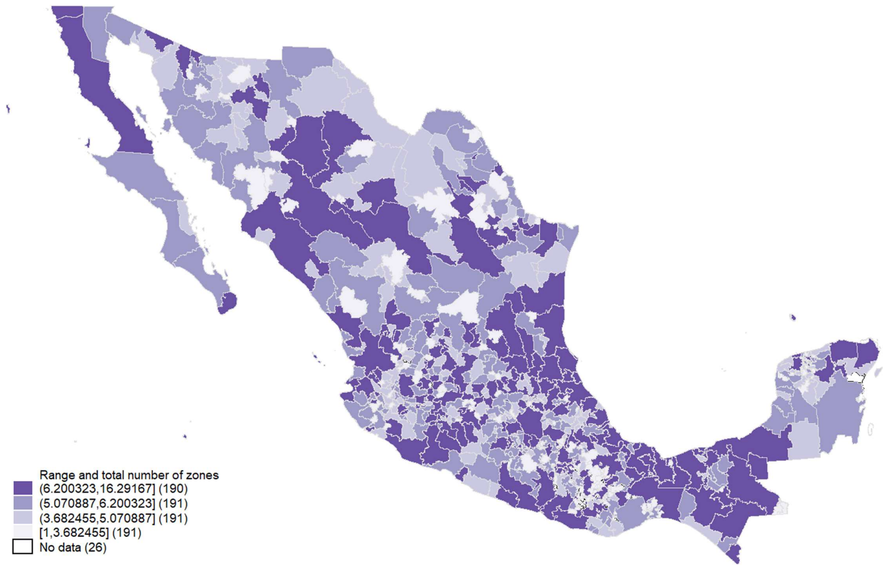
(b) Changes in mean wages unskilled 2000-2015



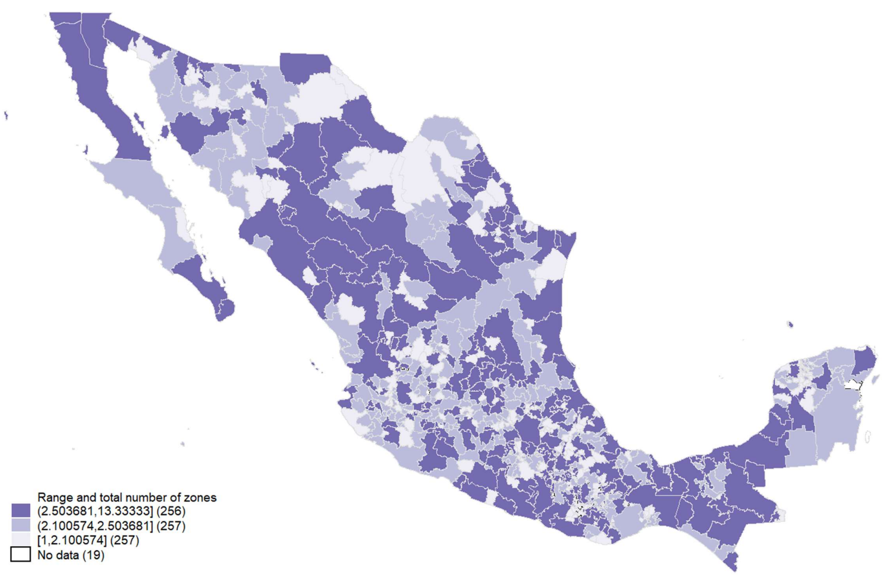
Source: Authors' calculations using data from the 2000 Population and Housing Census and the 2015 Inter-Censal Survey, INEGI.

Figure E6: Mean Inequality Measures

(a) P90/P10 2010



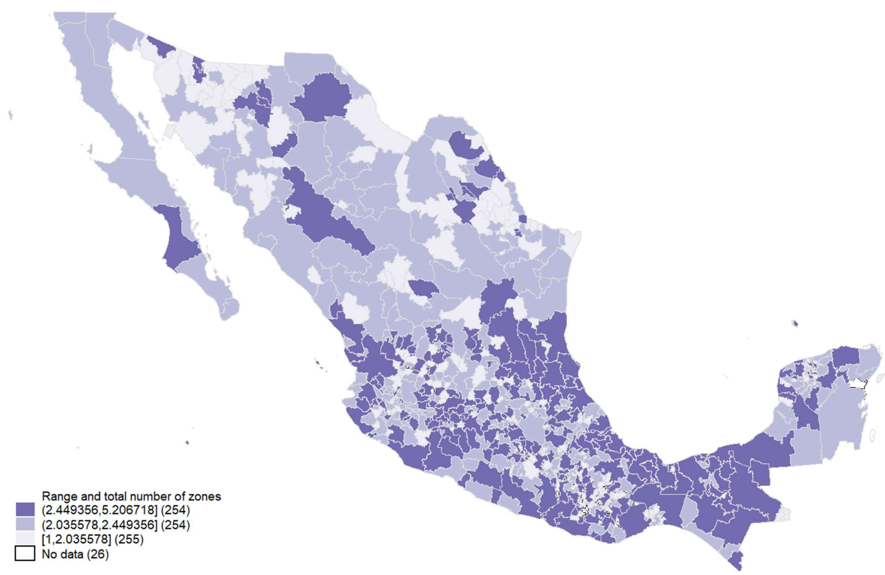
(b) P90/P50 2010



Source: Authors' calculations using data from the 2010 Population and Housing Census, INEGI.

Figure E6 Mean Inequality Measures: continued

(a) P50/P10 2010



Source: Authors' calculations using data from the 2010 Population and Housing Census, INEGI.

F Additional Tables

Table F1: Descriptive statistics

Variable	**mean**	**sd**	**p10**	**p50**	**p90**	**N**
1998/2000						
Economic Census data						
Wage share	0.32	0.47	0.00	0.20	0.71	29873
HHI	3,897.72	3,676.77	178.47	2,522.00	10,000.00	29873
Share top 5 firms (%)	72.95	32.94	18.28	93.26	100.00	29873
Wages/worker white collar	47.61	71.53	0.00	6.59	135.90	29873
Wages/worker blue collar	25.37	33.74	0.00	0.00	67.06	29873
Total workers	314.0	1,061.7	2.0	25.0	606.0	29873
Population and Housing Census data						
P90/P10	5.57	6.71	1.00	3.50	11.66	24549
P90/P50	2.39	1.79	1.00	1.95	4.13	24549
P50/P10	2.35	2.12	1.00	1.70	4.20	24549
gini	0.35	0.17	0.08	0.37	0.55	24549
informality rate	0.60	0.35	0.00	0.68	1.00	24549
gini monthly wage	0.38	0.19	0.09	0.39	0.62	24549
Migration flows	58.9	564.0	0.0	1.0	89.0	24549
Labor force	85,547.5	422,336.1	2,233.0	18,406.0	160,436.0	24549
Mean wage/hr skilled	65.5	539.2	16.2	44.1	104.1	24549
Mean wage/hr unskilled	35.7	83.0	12.3	25.1	55.9	24549
Mean monthly wage skilled	10,122.7	23,435.7	2,444.3	7,674.5	17,954.7	24549
Mean monthly wage unskilled	5,121.4	7,050.5	1,699.1	4,195.8	8,400.5	24549
2008/2010						
Economic Census data						
Wage share	0.38	0.49	0.00	0.28	0.84	32225
HHI	3,712.55	3,641.03	153.77	2,244.90	10,000.00	32225
Share top 5 firms (%)	71.14	33.48	16.88	89.24	100.00	32225
Wages/worker white collar	50.52	73.86	0.00	24.20	136.33	32225
Wages/worker blue collar	35.88	41.13	0.00	32.44	85.49	32225
Total workers	405.8	1,243.0	2.0	36.0	850.0	32225
Population and Housing Census data						
P90/P10	4.66	3.51	2.14	4.00	7.00	26101
P90/P50	2.06	0.86	1.33	1.95	2.80	26101
P50/P10	2.19	1.11	1.33	2.00	3.00	26101
gini	0.34	0.14	0.15	0.36	0.50	26101
informality rate	0.63	0.33	0.09	0.72	1.00	26101
gini monthly wage	0.36	0.16	0.16	0.36	0.53	26101
Migration flows	60.4	366.1	0.0	4.0	104.0	26101
Labor force	100,325.0	484,929.2	2,130.0	20,464.0	194,908.0	26101
Mean wage/hr skilled	56.5	54.2	22.1	44.9	94.4	26101
Mean wage/hr unskilled	37.4	44.7	17.4	30.3	56.6	26101
Mean monthly wage skilled	9,266.8	8,033.8	3,600.5	7,940.1	15,484.3	26101
Mean monthly wage unskilled	5,513.2	4,554.3	2,454.8	5,032.7	8,520.7	26101

Table F1 Descriptive statistics: continued

Variable	mean	sd	p10	p50	p90	N
		2013/2015				
		Economic Census data				
Wage share	0.33	0.37	0.00	0.24	0.76	33057
HHI	3,608.14	3,629.75	142.69	2,098.77	10,000.00	33057
Share top 5 firms (%)	69.84	33.84	16.00	85.96	100.00	33057
Wages/worker white collar	47.74	71.18	0.00	0.00	128.99	33057
Wages/worker blue collar	30.17	39.25	0.00	0.00	78.37	33057
Total workers	411.3	1,263.9	2.0	35.0	847.0	33057
		Population and Housing Census data				
P90/P10	5.53	84.62	2.14	4.00	7.00	11339
P90/P50	2.07	0.93	1.33	1.95	2.80	11339
P50/P10	2.45	23.53	1.33	2.00	3.00	11339
informality rate	0.61	0.33	0.11	0.67	1.00	11339
gini monthly wage	0.30	0.11	0.17	0.31	0.41	11339
Migration flows	53.2	368.8	0.0	4.0	81.0	11339
Labor force	98,203.1	473,229.3	1,978.0	19,781.0	194,800.0	11339
Mean monthly wage skilled	7,713.9	4,958.0	3,912.0	6,845.1	12,017.6	11339
Mean monthly wage unskilled	5,085.9	2,656.7	2,890.5	4,741.3	7,350.2	11339

*All variables are winsorized at the 1% and 99%
Source: Authors' calculations using data from the 1999, 2009, and 2014 Economic censuses as well as the 2000 and 2010 Population and Housing Census, and the Intercensal Survey 2015, INEGI.

Table F2: OLS estimates of the wage share and wages by skill level over labor market concentration

Dependent variable:	(1) Wage share	(2) ln(wages per worker) blue collar	(3) ln(wages per worker) white collar	(4) Wage share	(5) ln(wages per worker) blue collar	(6) ln(wages per worker) white collar
ln(HHI)	-0.0983	-0.109***	-0.143***			
	(0.108)	(0.0122)	(0.0115)			
Share top5				-0.00195	-0.00321***	-0.00432***
				(0.00430)	(0.000556)	(0.000530)
Fixed effects market level (NAICS 3-digits zone)	Yes	Yes	Yes	Yes	Yes	Yes
Time effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	121,783	121,783	121,783	121,783	121,783	121,783

** Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level
Robust standard errors clustered at the market level (NAICS 3-digits code-zone).
Source: Authors' calculations using data from the 1999, 2004, 2009, and 2014 Economic censuses.

Table F3: First stage IV estimates of the wage share and wages by skill level over labor market concentration

Dependent variable:	(1) ln(HHI)	(2) Share top 5
IV	0.558***	10.81***
	(0.0097)	(0.2232)
Fixed effects market level (NAICS 3-digits zone)	Yes	Yes
Time effects	Yes	Yes
F-statistic	3270.706	2344.965
Observations	115,493	115,493

** Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level
Robust standard errors clustered at the market level (NAICS 3-digits code-zone).
Source: Authors' calculations using data from the 1999, 2004, 2009, and 2014 Economic censuses.

Table F4: IV estimates of the wage share and wages by skill level over labor market concentration: controlling for one-employee firms

Dependent variable:	(1) Wage share	(2) ln(wages per worker) blue collar	(3) ln(wages per worker) white collar	(4) Skill premium	(5) Wage share	(6) ln(wages per worker) blue collar	(7) ln(wages per worker) white collar	(8) Skill premium
ln(HHI)	-0.0397***	-0.785***	-0.767***	0.0725***				
	(0.0140)	(0.0482)	(0.0508)	(0.0173)				
Share top 5					-0.00205***	-0.0406***	-0.0396***	0.00376***
					(0.000723)	(0.00253)	(0.00267)	(0.000902)
Fixed effects market level (NAICS 3-digits zone)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Share of one-employee firms	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-first stage	3288.682	3288.682	3288.682	1945.361	2358.545	2358.545	2358.545	2711.009
Observations	115,493	115,493	115,493	100,541	115,493	115,493	115,493	100,541

* Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level
Robust standard errors clustered at the market level (NAICS 3-digits code-zone).
Skill premium is measured as the logarithm of the ratio between white and blue-collar wages.
Source: Authors' calculations using data from the 1999, 2004, 2009, and 2014 Economic censuses.

Table F5: IV estimates of the wage share, wages, and inequality measures over labor market concentration: controlling for one-employee firms

Dependent variable:	(1) Δ ln(average wage skilled)	(2) Δ ln(average wage no skilled)	(3) Skill premium	(4) Δ P90/P10	(5) Δ P90/P50	(6) Δ P50/P10	(7) Δ gini
			Δ ln(HHI)				
Δ ln(HHI)	-0.115**	-0.132***	0.0359	1.098***	0.114*	0.344***	0.00630
	(0.0548)	(0.0388)	(0.0392)	(0.378)	(0.0666)	(0.128)	(0.00856)
Δ ln(migration inflows)	-0.00521***	-0.00401***	-0.00115***	-0.00312	-0.000432	0.000332	-0.000119
	(0.000358)	(0.000228)	(0.000231)	(0.00355)	(0.000619)	(0.00120)	(0.0000788)
Δ Informal rate	-0.0545**	-0.109***	0.0246	0.193	-0.0358	0.107	-0.0233***
	(0.0277)	(0.0206)	(0.0210)	(0.339)	(0.0604)	(0.115)	(0.00793)
Δ Share of one-employee firms	-0.0369	-0.0356**	0.00535	1.328***	0.286***	0.0461	0.0145
	(0.0246)	(0.0171)	(0.0175)	(0.391)	(0.0693)	(0.133)	(0.00884)
Time effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-first stage	1161.528	1161.528	828.965	576.366	576.366	576.366	576.366
			Δ Share top 5				
Δ Share top 5	-0.00618**	-0.00687***	0.00191	0.0603***	0.00626*	0.0188***	0.000274
	-0.00296	-0.00202	-0.00205	-0.0207	-0.00357	-0.007	-0.000461
Δ ln(migration inflows)	0.0370***	0.0260***	0.00873***	0.392***	0.00901***	0.172***	0.00842***
	-0.002	-0.00133	-0.0013	-0.0192	-0.00342	-0.00652	-0.000437
Δ Informal rate	-0.0569**	-0.110***	0.0251	0.152	-0.039	0.0953	-0.0229***
	-0.0279	-0.0206	-0.0212	-0.338	-0.0603	-0.115	-0.00792
Δ Share of one-employee firms	-0.0436*	-0.0429**	0.00693	1.577***	0.377***	0.101	0.0247***
	-0.0247	-0.0171	-0.0176	-0.395	-0.0704	-0.134	-0.00899
Time effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-first stage	719.267	719.267	558.64	943.16	943.16	943.16	943.16
Observations	48,820	48,820	37,821	17,372	17,372	17,372	17,372

* Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level
Robust standard errors clustered at the market level (NAICS 3-digits code-zone).
Source: Authors' calculations using data from the 1999, 2009, and 2014 Economic censuses, the 2000 and 2010 Population and Housing Census, and the Intercensal Survey 2015.
*Observations in columns (4) to (7) are lower as cells (combinations of NAICS sectors and zones) are too small in size.

Table F6: IV estimates of the wage share and wages by skill level over labor market concentration: excluding one-employee firms from the calculation of labor market concentration

Dependent variable:	**(1) Wage share**	**(2) ln(wages per worker) blue collar**	**(3) ln(wages per worker) white collar**	**(4) Skill premium**	**(5) Wage share**	**(6) ln(wages per worker) blue collar**	**(7) ln(wages per worker) white collar**	**(8) Skill premium**
ln(HHI)	-0.0531***	-1.040***	-0.970***	0.136***				
	(0.0147)	(0.0472)	(0.0495)	(0.0167)				
Share top 5					-0.00277***	-0.0542***	-0.0505***	0.00737***
					(0.000769)	(0.00252)	(0.00264)	(0.000915)
Fixed effects market level (NAICS 3-digits zone)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-first stage	3904.749	3904.749	3904.749	2306.906	2518.145	2518.145	2518.145	1549.957
Observations	104766	104766	104766	96,436	104766	104766	104766	96,436

* Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level
Robust standard errors clustered at the market level (NAICS 3-digits code-zone).
Skill premium is measured as the logarithm of the ratio between white and blue-collar wages.
Source: Authors' calculations using data from the 1999, 2004, 2009, and 2014 Economic censuses.

Table F7: IV estimates of the wage share, wages, and inequality measures over labor market concentration: excluding one-employee firms from the calculation of labor market concentration

Dependent variable:	(1) Δ Wage share	(2) Δ ln(average wage skilled)	(3) Δ ln(average wage no skilled)	(4) Skill premium	(5) Δ P90/P10	(6) Δ P90/P50	(7) Δ P50/P10	(8) Δ gini
				Δ ln(HHI)				
Δln(HHI)	-0.108***	-0.0948**	-0.120***	0.0336	1.613***	0.128**	0.471***	0.00651
	(0.0276)	(0.0395)	(0.0263)	(0.0281)	(0.341)	(0.0585)	(0.115)	(0.00758)
Δln(migration net inlows)	-0.000348	-0.00498***	-0.00352***	-0.00101***	-0.00250	-0.000104	0.000228	-0.0000991
	(0.000256)	(0.000357)	(0.000219)	(0.000233)	(0.00365)	(0.000630)	(0.00123)	(0.0000809)
ΔInformal rate	0.00790	-0.0763***	-0.122***	0.0221	0.329	-0.0625	0.169	-0.0285***
	(0.0137)	(0.0285)	(0.0201)	(0.0218)	(0.361)	(0.0634)	(0.122)	(0.00837)
Time effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-first stage	1436.578	1436.578	1436.578	1085.085	1573.804	1573.804	1573.804	1573.804
				ΔShare top 5				
ΔShare top 5	-0.00598***	-0.00563**	-0.00662***	0.00194	0.0995***	0.00792**	0.0290***	0.000406
	(0.00153)	(0.00235)	(0.00146)	(0.00162)	(0.0212)	(0.00363)	(0.00716)	(0.000473)
Δln(migration inflows)	-0.000267	-0.00487***	-0.00340***	-0.00105***	-0.00437	-0.000296	-0.000317	-0.000109
	(0.000258)	(0.000361)	(0.000221)	(0.000236)	(0.00376)	(0.000646)	(0.00127)	(0.0000830)
ΔInformal rate	0.00755	-0.0788***	-0.123***	0.0229	0.303	-0.0647	0.162	-0.0285***
	(0.0138)	(0.0287)	(0.0201)	(0.0219)	(0.363)	(0.0633)	(0.123)	(0.00837)
Time effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-first stage	854.15	854.15	854.15	792.008	996.971	996.971	996.971	996.971
Observations	48,820	48,820	48,820	37,046	17,372	17,372	17,372	17,372

* Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level
Robust standard errors clustered at the market level (NAICS 3-digits code-zone).
Source: Authors' calculations using data from the 1999, 2009, and 2014 Economic censuses, the 2000 and 2010 Population and Housing Census, and the Intercensal Survey 2015.
Observations in columns (5) to (8) are lower as cells (combinations of NAICS sectors and zones) are too small in size.

Table F8: Robustness: Long-term IV estimates of the wage share and wages by skill level over labor market concentration

Dependent variable:	(1) ln(wages per worker) blue collar	(2) ln(wages per worker) white collar	(3) Wage share	(4) ln(wages per worker) blue collar	(5) ln(wages per worker) white collar
ln(HHI)	-0.630***	-0.627***			
	(0.0589)	(0.0634)			
Share top5			-0.00232**	-0.0311***	-0.0310***
			(0.000961)	(0.00295)	(0.00316)
Fixed effects market level (NAICS 3-digits zone)	Yes	Yes	Yes	Yes	Yes
Time effects	Yes	Yes	Yes	Yes	Yes
F-first stage	2384.585	2384.585	1705.695	1705.695	1705.695
Observations	49,748	49,748	49,748	49,748	49,748

* Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level
Robust standard errors clustered at the market level (NAICS 3-digits code-zone).
Source: Authors' calculations using data from the 1999, 2014 Economic censuses.

Table F9: IV estimates of the wage share, wages, and inequality measures over labor market concentration: Robustness long term

Dependent variable:	(1) Δ Wage share	(2) **Δ ln(average wage skilled)**	(3) **Δ ln(average wage no skilled)**	(4) **Δ P90/P10**	(5) **Δ P90/P50**	(6) **Δ P50/P10**	(7) **Δ gini**
			Δ ln(HHI)				
Δ ln(HHI)	-0.124***	-0.151**	-0.190***	3.319***	0.480***	0.792***	0.0286***
	(0.0293)	(0.0725)	(0.0421)	(0.465)	(0.0812)	(0.149)	(0.0101)
Δ ln(migration inflows)	-0.00145***	-0.00801***	-0.00661***	-0.00314	0.000863	-0.00182	-0.000177**
	(0.000223)	(0.000563)	(0.000338)	(0.00388)	(0.000686)	(0.00125)	(0.0000854)
Δ Informal rate	-0.00681	-0.326***	-0.391***	1.346**	0.496***	0.124	-0.0192
	(0.0181)	(0.0660)	(0.0381)	(0.599)	(0.105)	(0.192)	(0.0132)
Time effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-first stage	1227.325	1227.325	1227.325	849.649	849.649	849.649	849.649
			Δ Share top 5				
Δ Share top 5	-0.307	-0.00833**	-0.0101***	0.196***	0.0297***	0.0461***	0.00167***
	(0.204)	(0.00402)	(0.00225)	(0.0282)	(0.00490)	(0.00893)	(0.000597)
Δ ln(migration inflows)	-0.0252	-0.00779***	-0.00635***	-0.00340	0.000420	-0.00197	-0.000211**
	(0.0305)	(0.000560)	(0.000335)	(0.00401)	(0.000707)	(0.00127)	(0.0000863)
Δ Informal rate	-0.411	-0.336***	-0.393***	1.186*	0.455***	0.0924	-0.0213
	(2.461)	(0.0672)	(0.0383)	(0.615)	(0.107)	(0.195)	(0.0131)
Time effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-first stage	955.938	955.938	955.938	589.994	589.994	589.994	589.994
Observations	22,257	22,257	22,257	8,581	8,581	8,581	8,581

* Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level
Robust standard errors clustered at the market level (NAICS 3-digits code-zone).
Source: Authors' calculations using data from the 1999, 2009, and 2014 Economic censuses, the 2000 and 2010 Population and Housing Census, and the Intercensal Survey 2015.
Observations in columns (4) to (7) are lower as cells (combinations of NAICS sectors and zones) are too small in size.

Table F10: IV estimates of the wage share, wages, and inequality measures over labor market concentration: Robustness long term (based on wage/hr)

Dependent variable:	(1) Δ Wage share	(2) Δ ln(average wage skilled/hr)	(3) Δ ln(average wage no skilled/hr)	(4) Δ P90/P10	(5) Δ P90/P50	(6) Δ P50/P10	(7) Δ gini
			Δ ln(HHI)				
Δ ln(HHI)	-0.124***	-0.0652	-0.0817***	1.256***	0.375***	0.178***	0.0125
	(0.0293)	(0.0436)	(0.0308)	(0.288)	(0.0922)	(0.0578)	(0.00924)
Δ ln(migration inflows)	-0.00145***	-0.00345***	-0.00362***	-0.00149	0.000423	-0.000500	-0.000199**
	(0.000223)	(0.000325)	(0.000241)	(0.00243)	(0.000777)	(0.000487)	(0.0000778)
Δ Informal rate	-0.00681	-0.0478	-0.0632**	1.229***	0.416***	0.0715	-0.00651
	(0.0181)	(0.0361)	(0.0248)	(0.372)	(0.119)	(0.0745)	(0.0120)
Time effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-first stage	1227.325	1227.325	1227.325	849.649	849.649	849.649	849.649
			Δ Share top 5				
Δ Share top 5	-0.307	-0.00370	-0.00433***	0.0726***	0.0230***	0.00930***	0.000700
	(0.204)	(0.00241)	(0.00163)	(0.0171)	(0.00550)	(0.00344)	(0.000545)
Δ ln(migration inflows)	-0.307	-0.00370	-0.00433***	0.0726***	0.0230***	0.00930***	0.000700
	(0.204)	(0.00241)	(0.00163)	(0.0171)	(0.00550)	(0.00344)	(0.000545)
Δ Informal rate	-0.411	-0.0557	-0.0634**	1.181***	0.395***	0.0688	-0.00706
	(2.461)	(0.0367)	(0.0249)	(0.372)	(0.119)	(0.0747)	(0.0119)
Time effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-first stage	955.938	955.938	955.938	589.994	589.994	589.994	589.994
Observations	22,257	22,257	22,257	8,581	8,581	8,581	8,581

* Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level
Robust standard errors clustered at the market level (NAICS 3-digits code-zone).
Source: Authors' calculations using data from the 1999, 2009, and 2014 Economic censuses, the 2000 and 2010 Population and Housing Census, and the Intercensal Survey 2015.
Observations in columns (4) to (7) are lower as cells (combinations of NAICS sectors and zones) are too small in size.

Table F11: IV estimates of the wage share, wages, and inequality measure over labor market concentration by sector:
Robustness share top 5

Dependent variable:	(1) Δ Wage share	(2) Δ ln(average wage skilled)	(3) Δ ln(average wage no skilled)	(4) Δ P90/P10	(5) Δ P90/P50	(6) Δ P50/P10	(7) Δ gini
Manufacturing							
Δ Share top 5	0.0577	-0.00457	-0.0212***	0.298***	0.0148	0.122***	0.000221
	(0.0675)	(0.0151)	(0.00814)	(0.102)	(0.0183)	(0.0371)	(0.00234)
Δ ln(migration inflows)	-0.00709	-0.00742***	-0.00377***	0.00643	0.00340**	-0.00168	0.000163
	(0.00514)	(0.00116)	(0.000550)	(0.00891)	(0.00161)	(0.00325)	(0.000211)
Δ Informal rate	0.167	-0.157*	-0.146***	0.324	0.0127	0.253	-0.0554***
	(0.231)	(0.0823)	(0.0477)	(0.896)	(0.137)	(0.327)	(0.0188)
Time effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-first stage	42.371	42.371	42.371	48.058	48.058	48.058	48.058
Observations	12,351	12,351	12,351	4,479	4,479	4,479	4,479
Services							
Δ Share top 5	-0.00242	-0.00834***	-0.00798***	0.0261	0.00268	0.00972	0.000116
	(0.00211)	(0.00316)	(0.00228)	(0.0240)	(0.00399)	(0.00811)	(0.000519)
Δ ln(migration inflows)	-0.000153	-0.00413***	-0.00341***	-0.0130***	-0.000925	-0.00261*	-0.000145
	(0.000317)	(0.000455)	(0.000316)	(0.00462)	(0.000772)	(0.00156)	(0.0000988)
Δ Informal rate	0.0104	-0.0279	-0.133***	0.703*	-0.0696	0.307**	-0.0145
	(0.0152)	(0.0321)	(0.0248)	(0.423)	(0.0733)	(0.143)	(0.00960)
Time effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-first stage	719.642	719.642	719.642	651.754	651.754	651.754	651.754
Observations	32,806	32,806	32,806	11,650	11,650	11,650	11,650

* Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level
Robust standard errors clustered at the market level (NAICS 3-digits code-zone).
Source: Authors' calculations using data from the 1999, 2009, and 2014 Economic censuses, the 2000 and 2010 Population and Housing Census, and the Intercensal Survey 2015.
Observations in columns (4) to (7) are lower as cells (combinations of NAICS sectors and zones) are too small in size.

Table F12: Probit model market had large entrants

Dependent variable	=1 if had large entrants
ln(population zone)	0.0109***
	(0.000374)
Distance to capital city	0.0104***
	(0.00158)
Distance to capital city2	-0.00381***
	(0.000812)
Average distance to regional capital	0.0000143
	(0.00000961)
% of population higher education	0.000516***
	(0.0000665)
% of households with drinking water	0.000110***
	(0.0000257)
% of households with phone	-0.0000147
	(0.0000412)
Technical school, junior college	-0.000708
	(0.000884)
% of households electricity	-0.0000474
	(0.0000479)
Banks	-0.00000604
	(0.0000254)
Kilometers of interstate	-0.000737
	(0.00275)
% employed in manufacturing	0.000220***
	(0.0000296)
Sectoral (NAICS 4 digits growth)	0.00235**
	(0.00101)
Observations	76850

* Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level
Robust standard errors clustered at the market level (NAICS 3-digits code-zone).
Source: Authors' calculations using data from the 2000 and 2010 Population and Housing Census.

Table F13: Estimates of the wage share, wages, and inequality measures over the number of entrants
controlling for lagged labor concentration

Dependent variable:	(1) Δ Wage share	(2) Δ ln(average wage skilled)	(3) Δ ln(average wage no skilled)	(4) Δ P90/P10	(5) Δ P90/P50	(6) Δ P50/P10	(7) Δ gini
Dummy large entrants	-0.000359	0.00622***	-0.000713	0.124***	0.0155***	0.0350***	0.000768*
	(0.000888)	(0.00164)	(0.00383)	(0.0186)	(0.00331)	(0.00629)	(0.000429)
Δ ln(migration inflows)	-0.000790***	-0.00538***	-0.00281***	-0.0138***	-0.00137*	-0.00354**	-0.000409***
	(0.000216)	(0.000405)	(0.000840)	(0.00462)	(0.000820)	(0.00156)	(0.000106)
Δ Informal rate	0.0290*	-0.0887***	-0.0757	-0.326	0.000390	-0.0658	-0.0201**
	(0.0157)	(0.0314)	(0.0552)	(0.339)	(0.0612)	(0.115)	(0.00808)
Lagged HHI	-0.000397	-0.00457***	-0.00241***	-0.0107**	-0.00173*	-0.00377**	-0.000635***
	(0.000254)	(0.000464)	(0.000820)	(0.00521)	(0.000921)	(0.00176)	(0.000119)
Time effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	48,820	48,820	48,820	17,372	17,372	17,372	17,372
Number of large entrants	-0.000112***	0.000229***	0.000110*	0.00175***	0.000470***	0.000311	0.0000676***
	(0.0000368)	(0.0000850)	(0.0000578)	(0.000651)	(0.000126)	(0.000220)	(0.0000164)
Δ ln(migration inflows)	-0.000660***	-0.00505***	-0.00289***	-0.00675	-0.000858	-0.00121	-0.000453***
	(0.000210)	(0.000932)	(0.000770)	(0.00452)	(0.000801)	(0.00153)	(0.000103)
Δ Informal rate	0.0287*	-0.0997	-0.0830	-0.450	-0.0130	-0.102	-0.0204**
	(0.0157)	(0.112)	(0.0534)	(0.339)	(0.0611)	(0.115)	(0.00807)
Lagged HHI	-0.000410	-0.00416***	-0.00231***	-0.0111**	-0.00178*	-0.00388**	-0.000634***
	(0.000254)	(0.00130)	(0.000797)	(0.00522)	(0.000921)	(0.00176)	(0.000119)
Time effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	48,820	48,820	48,820	17,372	17,372	17,372	17,372

* Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level
Robust standard errors clustered at the market level (NAICS 3-digits code-zone).
Source: Authors' calculations using data from the 1999, 2009, and 2014 Economic censuses, the 2000 and 2010 Population and Housing Census, and the Intercensal Survey 2015.
Observations in columns (4) to (7) are lower as cells (combinations of NAICS sectors and zones) are too small in size.

Table F14: Table 1 using pooled regression

Dependent variable:	(1) Wage share	(2) ln(wages per worker) blue collar	(3) ln(wages per worker) white collar	(4) Wage share	(5) ln(wages per worker) blue collar	(6) ln(wages per worker) white collar
			Pooled regression			
ln(HHI)	-0.0780**	-0.542***	-0.431***			
	(0.0308)	(0.109)	(0.116)			
Share top 5				-0.00397**	-0.0276***	-0.0220***
				(0.00157)	(0.00558)	(0.00596)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time effects	Yes	Yes	Yes	Yes	Yes	Yes
Sector effects	Yes	Yes	Yes	Yes	Yes	Yes
F-first stage	159.462	159.462	159.462	138.475	138.475	138.475
Observations	121,783	121,783	121,783	121,783	121,783	121,783

* Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level
Robust standard errors clustered at the market level (NAICS 3-digits code-zone).
Source: Authors' calculations using data from the 1999, 2004, 2009, and 2014 Economic censuses.
Controls include ln(migration) and the informality rate.

Table F15: Table 2 using pooled regression

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:	Wage share	ln(average wage skilled)	ln(average wage no skilled)	P90/P10	P90/P50	P50/P10	gini
			ln(HHI)				
ln(HHI)	-0.0848*	0.238	-0.208**	0.691*	0.138*	0.201*	-0.00220
	(0.0491)	(0.188)	(0.0903)	(0.358)	(0.0765)	(0.115)	(0.0161)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	No	No	No	No	No	No	No
F-first state	40.627	40.627	40.627	248.82	248.82	248.82	248.82
			Share top 5				
Share top 5	-0.00494*	0.0134	-0.0119**	0.0384*	0.00760*	0.0108*	-0.0000396
	(0.00270)	(0.0106)	(0.00527)	(0.0201)	(0.00439)	(0.00646)	(0.000916)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	No	No	No	No	No	No	No
F-first state	26.386	26.386	26.386	184.683	184.683	184.683	184.683
Observations	78,523	78,523	78,523	45,048	45,048	45,048	45,048

* Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level
Robust standard errors clustered at the market level (NAICS 3-digits code-zone).
Source: Authors' calculations using data from the 1999, 2009, and 2014 Economic censuses, the 2000 and 2010 Population and Housing Census, and the Intercensal Survey 2015.
Observations in columns (4) to (7) are lower as cells (combinations of NAICS sectors and zones) are too small in size.

Table F16: IV estimates of the wage share and wages by skill level over labor market concentration: excluding large cities

Dependent variable:	(1) Wage share	(2) ln(wages per worker) blue collar	(3) ln(wages per worker) white collar	(4) Skill premium	(5) Wage share	(6) ln(wages per worker) blue collar	(7) ln(wages per worker) white collar	(8) Skill premium
Excluidng CDMX								
ln(HHI)	-0.0428***	-0.803***	-0.788***	0.0683***				
	(0.0143)	(0.0496)	(0.0523)	(0.0175)				
Share top 5					-0.00222***	-0.0417***	-0.0409***	0.00354***
					(0.000743)	(0.00263)	(0.00277)	(0.000909)
Fixed effects market level (NAICS 3-digits zone)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-first stage	3186.327	3186.327	3186.327	1864.773	2265.035	2265.035	2265.035	1487.814
Observations	110918	110918	110918	73436	110918	110918	110918	73436
Excluidng CDMX, Jalisco, and Nuevo León								
ln(HHI)	-0.0413***	-0.768***	-0.749***	0.0772***				
	(0.0150)	(0.0511)	(0.0542)	(0.0181)				
Share top 5					-0.00211***	-0.0392***	-0.0382***	0.00397***
					(0.000763)	(0.00265)	(0.00281)	(0.000937)
Fixed effects market level (NAICS 3-digits zone)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-first stage	3186.327	2748.491	2748.491	1679.646	2265.035	2027.537	2027.537	1360.745
Observations	110918	110918	110918	73436	110918	110918	110918	73436

* Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level
Robust standard errors clustered at the market level (NAICS 3-digits code-zone).
Skill premium is measured as the logarithm of the ratio between white and blue-collar wages.
Source: Authors' calculations using data from the 1999, 2004, 2009, and 2014 Economic censuses.

Table F17: IV estimates of the wage share, wages, and inequality measures over labor market concentration: excluding large cities

Dependent variable:	(1) △ Wage share	(2) △ ln(average wage skilled)	(3) △ ln(average wage no skilled)	(4) Skill premium	(5) △ P90/P10	(6) △ P90/P50	(7) △ P50/P10	(8) △ gini
				△ ln(HHI)				
△ ln(HHI)	-0.0185	-0.0662	-0.108***	0.0492	0.710	0.0676	0.256*	0.00594
	(0.0377)	(0.0587)	(0.0420)	(0.0413)	(0.452)	(0.0828)	(0.152)	(0.0104)
△ ln(migration net inlows)	-0.000155	-0.00497***	-0.00396***	-0.00110***	-0.00885**	-0.00107	-0.00107	-0.000150
	(0.000251)	(0.000392)	(0.000257)	(0.000253)	(0.00417)	(0.000741)	(0.00140)	(0.0000930)
△ Informal rate	-0.00579	-0.0432	-0.101***	0.0298	-0.368	-0.0560	-0.0231	-0.0154**
	(0.0127)	(0.0303)	(0.0230)	(0.0224)	(0.308)	(0.0556)	(0.103)	(0.00725)
Time effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-first stage	669.263	669.263	669.263	502.468	903.634	903.634	903.634	903.634
				△ Share top 5				
△ Share top 5	-0.000960	-0.00362	-0.00578***	0.00267	0.0402	0.00462	0.0140*	0.000267
	(0.00196)	(0.00323)	(0.00223)	(0.00222)	(0.0250)	(0.00473)	(0.00838)	(0.000594)
△ ln(migration inflows)	-0.000132	-0.00487***	-0.00382***	-0.00119***	-0.00917**	-0.00102	-0.00126	-0.000140
	(0.000262)	(0.000416)	(0.000270)	(0.000273)	(0.00418)	(0.000744)	(0.00140)	(0.0000932)
△ Informal rate	-0.00579	-0.0449	-0.102***	0.0308	-0.384	-0.0587	-0.0269	-0.0151**
	(0.0127)	(0.0306)	(0.0231)	(0.0226)	(0.308)	(0.0557)	(0.103)	(0.00724)
Time effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-first stage	462.015	462.015	462.015	351.343	569.624	569.624	569.624	569.624
Observations	40065	40065	40065	26332	16727	16727	16727	16727

* Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level
Robust standard errors clustered at the market level (NAICS 3-digits code-zone).
Source: Authors' calculations using data from the 1999, 2009, and 2014 Economic censuses, the 2000 and 2010 Population and Housing Census, and the Intercensal Survey 2015.
Observations in columns (5) to (8) are lower as cells (combinations of NAICS sectors and zones) are too small in size.

Table F18: IV estimates of the wage share , wages , and inequality measures over labor market concentration: excluding Mexico City

Dependent variable:	(1) Δ Wage share	(2) Δ ln(average wage skilled)	(3) Δ ln(average wage no skilled)	(4) Skill premium	(5) Δ P90/P10	(6) Δ P90/P50	(7) Δ P50/P10	(8) Δ gini
				Δ ln(HHI)				
Δ ln(HHI)	-0.0455	-0.0942*	-0.137***	0.0524	0.421	-0.0374	0.209	-0.0278***
	(0.0360)	(0.0566)	(0.0396)	(0.0404)	(0.405)	(0.0767)	(0.138)	(0.00981)
Δ ln(migration net inlows)	-0.000204	-0.00509***	-0.00402***	-0.00113***	-0.00590	-0.00148**	0.000250	-0.0000109
	(0.000234)	(0.000368)	(0.000235)	(0.000237)	(0.00391)	(0.000709)	(0.00133)	(0.0000907)
Δ Informal rate	-0.00259	-0.0459	-0.106***	0.0341	0.0337	-0.0539	0.119	-0.0254***
	(0.0118)	(0.0282)	(0.0209)	(0.0213)	(0.315)	(0.0578)	(0.107)	(0.00766)
Time effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-first stage	767.171	767.171	767.171	554.182	1054.728	1054.728	1054.728	1054.728
				Δ Share top 5				
Δ Share top 5	-0.00238	-0.00519*	-0.00729***	0.00284	0.0240	-0.00155	0.0114	-0.00164***
	(0.00188)	(0.00313)	(0.00211)	(0.00217)	(0.0223)	(0.00438)	(0.00760)	(0.000561)
Δ ln(migration inflows)	-0.000149	-0.00493***	-0.00383***	-0.00123***	-0.00626	-0.00137*	0.00000837	0.0000221
	(0.000244)	(0.000390)	(0.000246)	(0.000256)	(0.00392)	(0.000711)	(0.00134)	(0.0000911)
Δ Informal rate	-0.00287	-0.0487*	-0.108***	0.0352	0.0290	-0.0550	0.119	-0.0251***
	(0.0119)	(0.0285)	(0.0210)	(0.0215)	(0.314)	(0.0579)	(0.107)	(0.00769)
Time effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-first stage	524.857	833.341	524.857	384.533	691.652	691.652	691.652	691.652
Observations	46817	46817	46817	33478	16941	16941	16941	16941

* Significant at the 10% level, ** Significant at the 5% level, *** Significant at the 1% level
Robust standard errors clustered at the market level (NAICS 3-digits code-zone).
Source: Authors' calculations using data from the 1999, 2009, and 2014 Economic censuses, the 2000 and 2010 Population and Housing Census, and the Intercensal Survey 2015.
Observations in columns (5) to (8) are lower as cells (combinations of NAICS sectors and zones) are too small in size.