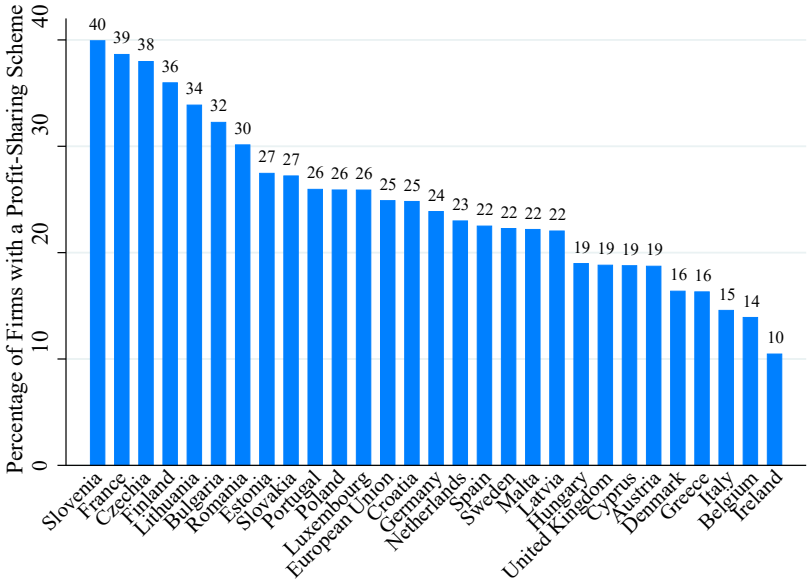
Supplementary Appendix: For Online Publication Only

This appendix contains additional information and analyses. Appendix A reports the results of secondary analyses, including additional figures and tables. In Appendix B, we present evidence of patterns of outsourcing across different types of establishments. Appendix C details our markdown estimation procedure. Appendix D reports the results of a battery of robustness checks for key empirical results in the main body of the paper.

A Supplementary Analyses

A.1 Additional Figures and Tables

Figure A.1: Prevalence of Profit-Sharing Schemes in Advanced Economies, 2019



Notes: This figure reports the prevalence of profit-sharing schemes for companies in the European Union and the United Kingdom.
Source: Authors' elaboration using data from the European Company Survey, 2019.

Table A.1: Average Labor Markdown by Industry and Census Wave

Industry	1999	2004	2009	2014	2019
	(1)	(2)	(3)	(4)	(5)
Transportation equipment	1.97	1.7	2.02	1.83	1.92
	(0.06)	(0.05)	(0.06)	(0.06)	(0.06)
Machinery	1.91	1.67	1.61	1.67	1.89
	(0.07)	(0.05)	(0.06)	(0.07)	(0.06)
Food	2.16	1.68	1.56	1.66	1.74
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Chemical	1.7	1.63	1.73	1.64	1.67
	(0.04)	(0.03)	(0.04)	(0.04)	(0.03)
Nonmetallic mineral products	1.39	1.21	1.16	1.22	1.58
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Petroleum and coal products	1.62	1.64	1.7	1.6	1.54
	(0.07)	(0.05)	(0.07)	(0.08)	(0.09)
Miscellaneous	1.6	1.43	1.37	1.23	1.5
	(0.05)	(0.04)	(0.03)	(0.03)	(0.03)
Plastics and rubber products	1.56	1.37	1.52	1.35	1.49
	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)
Electrical equipment, appliances, and components	1.75	1.57	1.7	1.4	1.47
	(0.06)	(0.05)	(0.06)	(0.05)	(0.05)
Fabricated metal products	1.48	1.32	1.19	1.15	1.34
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Paper	1.2	1.18	1.22	1.18	1.23
	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)
Apparel	1.41	1.36	1.19	1.21	1.19
	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
Primary metal	1.22	1.21	1.01	1.01	1.18
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Wood products	1.15	1.08	0.98	0.93	1.05
	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
Leather and allied product	1.02	1.16	0.84	0.89	0.97
	(0.12)	(0.13)	(0.08)	(0.06)	(0.07)
Printing and related support activities	0.9	0.86	0.8	0.75	0.94
	(0.06)	(0.01)	(0.01)	(0.01)	(0.01)
Beverage and tobacco products	0.9	0.89	0.83	0.86	0.74
	(0.01)	(0.01)	(0.004)	(0.004)	(0.003)
Computer and electronic products	0.59	0.52	0.55	0.51	0.62
	(0.05)	(0.04)	(0.05)	(0.03)	(0.04)
Furniture and related products	0.48	0.46	0.46	0.43	0.5
	(0.01)	(0.01)	(0.01)	(0.01)	(0.004)
Total	1.8	1.47	1.37	1.4	1.5
	(0.007)	(0.005)	(0.005)	(0.004)	(0.004)

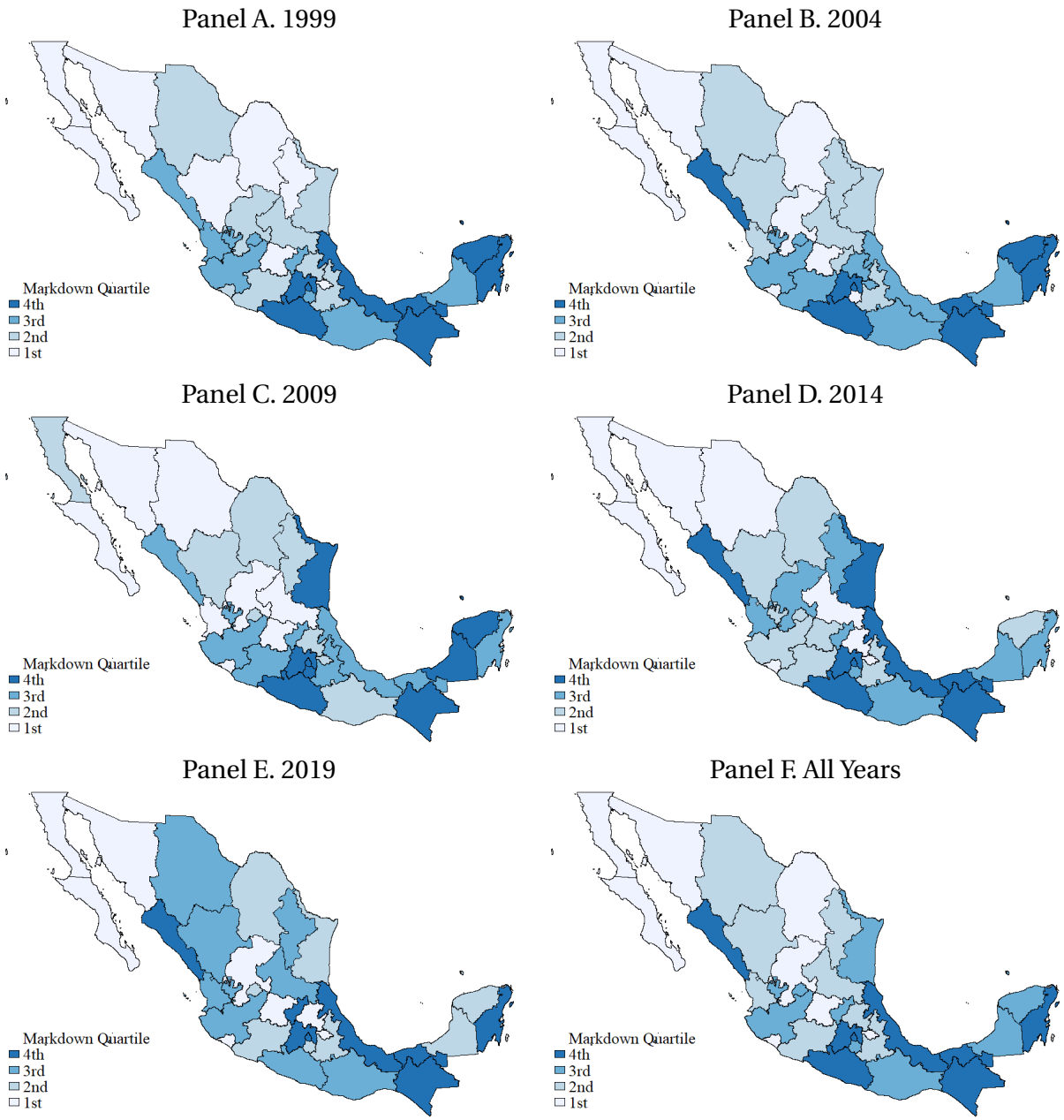
Notes: We estimate markdowns assuming that the production function is translog with parameters that vary at the industry group level. Industry groups are defined by 3-digit 1997 NAICS codes for manufacturing industries. Industries are sorted in descending order according to their average markdown in 2019. Standard errors are in parentheses.
Source: Authors' elaboration using data from the Mexican economic census.

Table A.2: Average Labor Markdown by Country Region and Census Wave

Region	1999	2004	2009	2014	2019	Total
	(1)	(2)	(3)	(4)	(5)	(6)
Central	1.89	1.55	1.44	1.49	1.57	1.57
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
South	1.9	1.56	1.43	1.46	1.55	1.54
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
North	1.67	1.36	1.3	1.33	1.45	1.41
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Bajío	1.75	1.41	1.31	1.32	1.44	1.42
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Total	1.8	1.47	1.37	1.4	1.5	1.49
	(0.007)	(0.005)	(0.005)	(0.004)	(0.004)	(0.002)

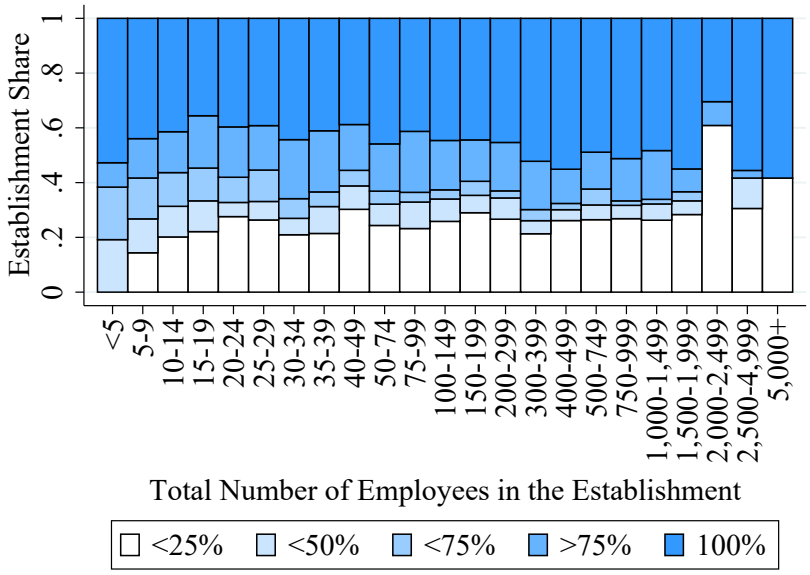
Notes: The North region includes Baja California, Baja California Sur, Coahuila, Chihuahua, Durango, Nuevo León, Sinaloa, Sonora, and Tamaulipas. The *Bajío* region includes Aguascalientes, Colima, Guanajuato, Jalisco Michoacán, Nayarit, Querétaro, San Luis Potosí, and Zacatecas. The Center region includes Mexico City, Hidalgo, Estado de México, Morelos, Puebla, Tlaxcala, and Veracruz. The South region includes Campeche, Chiapas, Guerrero, Oaxaca, Quintana Roo, Tabasco, and Yucatán. Regions are ranked according to their average labor markdown in 2019. We estimate markdowns assuming that the production function is translog with parameters that vary at the 3-digit industry level. Industry groups are defined by 3-digit 1997 NAICS codes for manufacturing industries. Standard errors are in parentheses.
Source: Authors' elaboration using data from the Mexican economic census.

Figure A.2: Average Markdown in Manufacturing by State and Census Wave



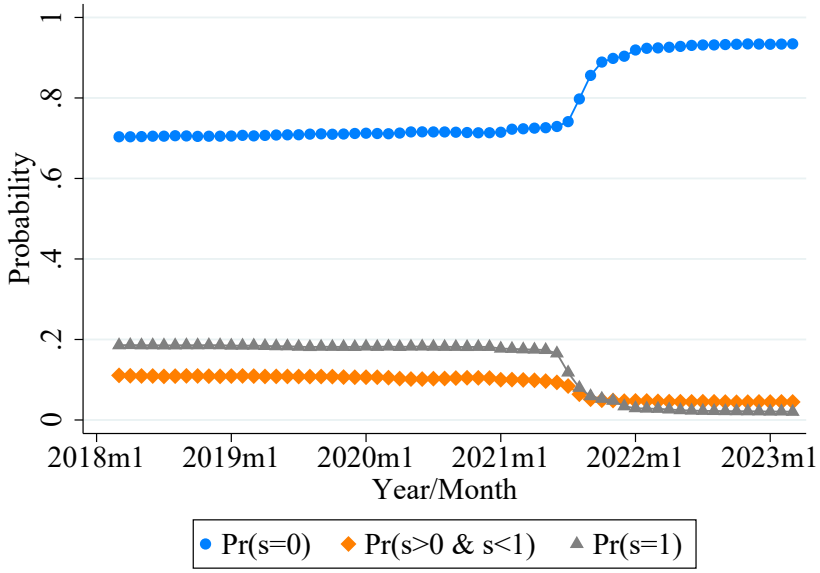
Notes: Each shade in the figure denotes a different quartile of the average markdown distribution, with lighter shades representing lower quartiles and darker shades representing higher quartiles. Quartiles in Panels A through E are taken with respect to the cross-sectional distribution of average markdowns at the state level by year, whereas Panel F depicts quartiles with respect to the distribution of average markdowns taken over all establishments and years at the state level. We estimate markdowns assuming that the production function is translog with parameters that vary at the 3-digit 1997 NAICS industry code level.
Source: Authors' elaboration using data from the Mexican economic census.

Figure A.3: Distribution of Outsourced Employee Percentages by Establishment Size, 2019



Notes: This figure presents the distribution of outsourced employee percentages by establishment size, conditional on hiring at least one employee through outsourcing, for the universe of manufacturing establishments that keep employment and wage accounts and report positive labor, capital, raw materials, and energy usage in 2019.
Source: Authors' elaboration using data from the Mexican economic census.

Figure A.4: Outsourcing Probabilities at the Establishment Level, 2018–2023

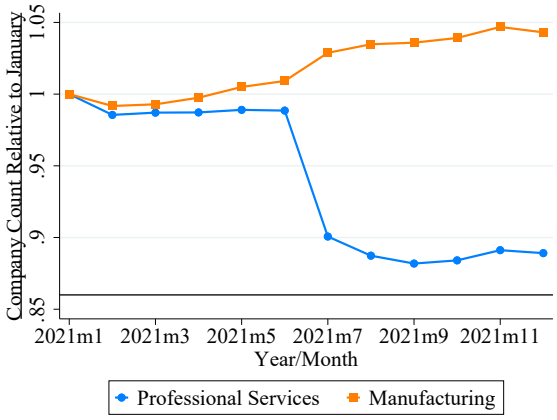


Notes: This figure presents the probability that an establishment hires a share $s \in [0,1]$ of its employees through outsourcing from 2018 to 2023.
Source: Authors' elaboration using data from the Mexican monthly manufacturing survey from 2018 to 2023.

A.2 IMSS Data

This section uses IMSS matched hirer–employee data from 2021 to test the reform's impact on the employment status and registered wages of previously outsourced workers. These data are at monthly frequency and are available for the universe of formal workers, but we focus on workers hired either in manufacturing or by a staffing company in March 2021, the month before the reform was enacted. While no reliable registry of shell staffing companies existed before the reform, they can be indirectly identified using IMSS data, albeit imperfectly, as those fulfilling two conditions: (1) being registered in the "provision of professional services to other firms" sector within the IMSS economic sector classifier and (2) permanently exiting the market in July 2021. The first condition captures the fact that IMSS officials registered all companies supplying professional services to other firms in the specified sector, including those providing legitimate professional services (e.g., accounting) and those hiring the core employees of other firms for social security evasion and profit-sharing avoidance purposes. The second condition captures the last month of the reform's grace period during which shell outsourcing companies had to exit the market and employing firms had to hire previously outsourced workers directly. Figure A.5 shows that the number of firms registered in the "provision of professional services to other firms" sector abruptly dropped in July 2021 but did not do so in the manufacturing sector.

Figure A.5: Drop in the Number of Companies in the Professional Services Sector of IMSS



Notes: This figure presents the number of active companies registered with the IMSS in the "professional services to other firms" and manufacturing sectors relative to their levels in January for each month of 2021.
Source: Authors' elaboration using matched hirer–employee data from the IMSS for 2021.

Using this proxy strategy to identify shell staffing companies, we test two hypotheses rele-

vant to our main empirical results. First, data on employment status allow us to test whether, after the reform, previously outsourced workers were *less* likely to remain formally employed and, in particular, employed in manufacturing, than workers directly hired in manufacturing before the reform. While we have shown that the reform had null impacts on employment levels in our main empirical analysis, testing this possibility is crucial because the establishment-level data from the manufacturing survey do not allow us to reject the possibility that outsourced workers were terminated and replaced with other workers after the reform. If this proved to be the case, we would expect to see a widening of the gap in the likelihood of being employed by a formal manufacturing company between the group of workers directly hired in manufacturing and the group contracted through outsourcing before the reform because terminated workers would be more likely to be unemployed after the reform. Second, the registered average monthly wage data allow us to test effects on social security payments at the worker level. If the reform operated by increasing the nonsalary labor costs associated with previously outsourced workers, we would expect the reform to increase their registered wage relative to the wage of workers directly hired before the reform.

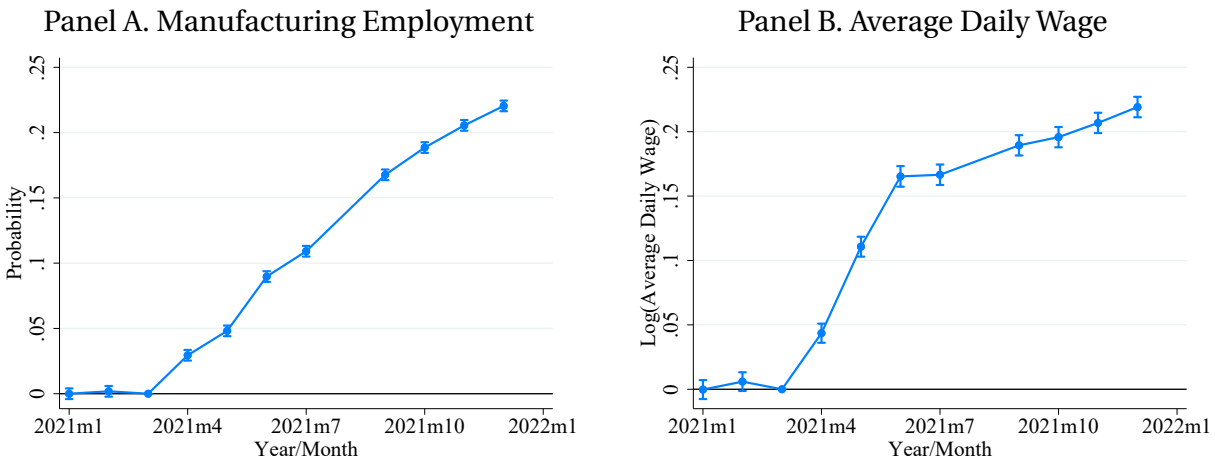
To test these hypotheses, we follow an empirical strategy similar to that in our main analysis. In particular, we estimate via OLS the effect of the reform on the outcome of interest Y_{it} after j months, given by the parameter β_j in the following differences-in-differences model:

$$Y_{it} = \sum_{j=\text{January 2021}}^{\text{December 2021}} [\mathbb{1}_{t=t_0+j} \times \text{Staffing}_{i,t_0}]\beta_j + \text{Staffing}_{i,t_0}\gamma + \delta_t + \varepsilon_{it}, \tag{2}$$

where $\text{Staffing}_{i,t_0}$ is an indicator for the event of worker i being hired by a shell staffing company at t_0, the period immediately prior to the reform; γ is a group fixed effect, which absorbs all time-invariant variation in the outcome of interest for workers hired by shell staffing companies at t_0; δ_t is a time dummy, which absorbs all aggregate shocks that affect outcomes equally across all workers; and ε_{it} is an idiosyncratic unobserved shock to the outcome of interest. Standard errors are robust to heteroskedasticity of unknown form. In estimation, we exclude the interaction between our shell staffing company indicator and the dummy for March 2021, allowing us to interpret our coefficient estimates as deviations in the outcome of interest relative to the level observed for the group of directly hired workers in manufacturing before the

reform.

Figure A.6: Testing for Pretrends in Registration Outcomes



Notes: This figure presents the regression coefficients and 95 percent confidence intervals of month dummies interacted with an indicator for the event of the worker being employed at a shell staffing company in March 2021, controlling for month dummies and the same indicator. Each panel presents results for a different outcome. Standard errors are robust to heteroskedasticity of unknown form. The interaction for March 2021 is excluded from each regression, so the effects can be interpreted as deviations from the outcome mean of the comparison group in the month prior to the 2021 reform.
Source: Authors' elaboration using matched employer–employee data from the IMSS for 2021.

The parallel trends assumption required to lend a causal interpretation to the OLS estimates of the parameters of Equation (2) is that the outcomes of interest would have followed the same trend for previously outsourced workers and directly hired workers in the manufacturing sector in the absence of the reform. Figure A.6 provides evidence supporting the validity of this assumption. As expected, both the probability of being employed by a manufacturing company and the registered average monthly wage uninterruptedly rose after the reform from May to December 2021. Table A.3 reports the end-of-year OLS impact estimates of the reform. It shows that the probability of being formally employed by a manufacturing company rose by 22 percentage points (p=0.000) and that the registered average monthly wage increased by 22 percent (p=0.000) for previously outsourced workers relative to their counterparts for workers directly hired by a manufacturing company before the reform.

Table A.3: Effects of the Reform on Registration Outcomes

	Employment in Manufacturing	Log(Average Monthly Wage)
Regressor	(1)	(2)
$\text{Staffing}_{i,2020} \times \text{Post}_t$	0.22***	0.22***
	(0.002)	(0.004)
N	78,935,384	72,496,441
R^2	0.041	0.008

Notes: The effects shown correspond to impacts in December 2021. The measure of cross-sectional exposure to the reform is an indicator for the event of the worker being employed at a shell staffing company in March 2021. Standard errors are robust to heteroskedasticity of unknown form. ***p<0.01.
Source: Authors' elaboration using matched hirer–employee data from the IMSS for 2021.

A.3 Reform's Impacts on Investment Perspectives

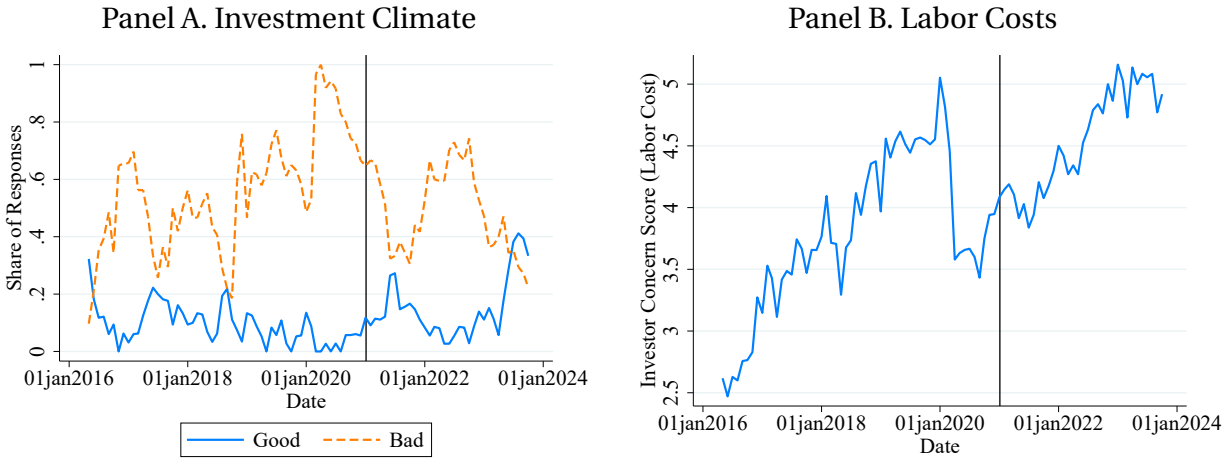
To formally examine the reform's impacts on investors' appetite for investing in Mexico, we utilize monthly data from the central bank's private sector perceptions survey, the *Encuesta sobre las expectativas de los especialistas en economía del sector privado* (EEEESP) from 2016 to 2023. This survey interviews between 30 and 97 private sector analysts from national and international commercial banks and economic consulting groups every month about the business outlook for Mexico, including their expectations for future inflation, GDP growth, interest and exchange rates, the balance of payments, and the general investment environment. We test whether the reform led to a structural break in interviewees' answers to the following questions: "How would you rate the current business environment for investors to make new investments in Mexico (Good, Bad, Not Sure)?" and "In the next six months, how much of a constraint do labor costs present on the growth of economic activity in Mexico on a scale of 1 to 7?" Figure A.7 depicts the time series of the interviewees' mean responses to these questions. While both time series are nonstationary, we cannot visually detect a structural break in any of them. Nonetheless, we formally test for a structural break after the reform, which was enacted in April 2021, by estimating the parameter β of the following regression model via OLS:

$$\Delta Y_t = \alpha + \mathbb{1}_{\{t>\text{April 2021}\}}\beta + \varepsilon_t, \tag{3}$$

where Y_t is the mean response of the interviewees to the question of interest at time t and ε_t is an error term. Standard errors are robust to heteroskedasticity of unknown form and to autocorrelation of up to one lag, estimated using the methodology in Newey and West (1987). Table

A.4 shows the results of this exercise. We find no evidence of structural breaks in interviewees' perceptions about the investment environment and the burden of labor costs after the reform.

Figure A.7: Investor Perceptions of Investment Climate in Mexico



Notes: This figure presents the average responses of national and international economic analysts and consultants from the private sector to two monthly questions regarding the investment climate and labor costs in Mexico from 2016 to 2023. Panel A depicts the share of respondents who answered "Good" or "Bad" to the question "How would you rate the current business environment for investors to make new investments in Mexico (Good, Bad, Not Sure)?" Panel B depicts the average response to the question "In the next six months, how much of a constraint do labor costs present on the growth of economic activity in Mexico on a scale of 1 to 7?" The vertical black line in each panel represents April 24, 2021, the enactment date of the domestic outsourcing reform.
Source: Authors' elaboration using data from the Mexican central bank's private sector perceptions survey.

Table A.4: Tests for Structural Breaks in Survey Responses after the Outsourcing Reform

Regressor	Investment Climate		Labor Cost
	Good	Bad	
	(1)	(2)	(3)
$\mathbb{1}_{t >$ April 2021$\}$	0.011	-0.020	0.002
	(0.013)	(0.022)	(0.039)
N	89	89	89
Outcome Mean	0.113	0.535	4.068

Notes: Standard errors are robust to heteroskedasticity of unknown form and autocorrelation of up to one lag.
Source: Authors' elaboration using data from the Mexican central bank's private sector perceptions survey from May 2016 to October 2023.

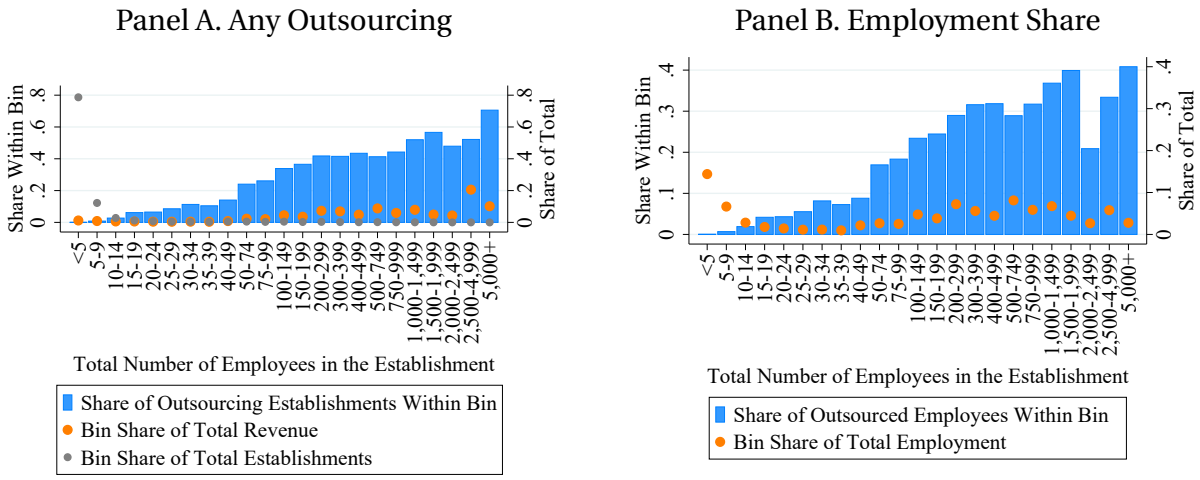
B Outsourcing Patterns by Firm Type

B.1 Large Firms', Foreign Firms', and *Maquiladoras*' Outsourcing

We present visual and regression evidence that the prevalence of outsourcing is higher for large establishments than for small establishments. First, Figure B.1 shows that outsourc-

ing increases with the total number of employees in the establishment. Specifically, Panel A shows that the share of establishments that employ at least one outsourced employee on their premises increases monotonically with total employment. Similarly, Panel B reports a positive gradient in the share of outsourced employees with total employment.

Figure B.1: Outsourcing Prevalence by Establishment Size, 2019



Notes: This figure presents the prevalence of outsourcing by establishment size for the universe of manufacturing establishments that keep employment and wage accounts and report positive labor, capital, raw materials, and energy usage in 2019. Panel A reports the share of establishments that hire at least one of their employees through outsourcing by establishment size bin, as well as each bin's share of the total number of establishments and the bin's share of establishment revenue in the manufacturing sector. Panel B reports the share of outsourced employees by establishment size bin, as well as each bin's share of total employment in the manufacturing sector.
Source: Authors' elaboration using data from the Mexican economic census.

The regression results reported in Table B.1 show that this relationship also exists at the establishment level, under the same and alternative establishment size measures, even after we control for industry and year dummies. Column (1) shows that a 1 percent increase in the total employee count is associated with an increase in the establishment's share of outsourced workers of 1 percentage point (p=0.000). Columns (2) through (4) show strongly significant correlations between the share of outsourced workers in the establishment and the establishment's local labor market employment share, the log of establishment revenue, and the local labor market revenue share of the establishment, respectively.

The table also shows that foreign-owned manufacturing establishments, which proliferated with the rise in FDI after the enactment of NAFTA (Cuevas, Messmacher and Werner, 2005), display a higher share of outsourced employees than domestic establishments. The correlation between foreign ownership and outsourcing is of interest because a well-documented regularity

in the trade literature is that firms receiving FDI are larger and more productive than other firms (see Helpman, 2006). Besides their size and propensity to receive FDI, foreign-owned firms may have greater bargaining power vis-à-vis local workers than other establishments because of the credible threat that they might relocate their operations if labor costs rise.

Table B.1: Outsourcing and Establishment Size
Outcome Variable: Share of Outsourced Employees

Regressor	By Establishment Size				By Foreign Ownership	
	(1)	(2)	(3)	(4)	(5)	(6)
Log(Total Employee Count)	0.01***					
	(0.0006)					
Employment Share of Local Labor Market		0.07***				
		(0.005)				
Log(Total Revenue)			0.01***			
			(0.0007)			
Revenue Share of Local Labor Market				0.07***		
				(0.004)		
Foreign Ownership					0.05***	0.05***
					(0.003)	(0.003)
Foreign Ownership × Maquiladora						0.02***
						(0.005)
Maquiladora						0.0003
						(0.001)
N	230,185	230,185	230,185	230,185	230,185	230,185
R^2	0.109	0.09	0.122	0.091	0.124	0.124

Notes: All regressions include market fixed effects and time dummies. Standard errors are robust to heteroskedasticity of unknown form and are clustered at the market level. ***p<0.01.
Source: Authors' elaboration using data from the Mexican economic census waves from 1994 to 2019.

Column (5) of the table shows that the share of outsourced employees is 5 percentage points higher among foreign-owned establishments than among domestic establishments. Moreover, we construct an indicator for *maquiladora* establishments, which host the manufacturing operations of American firms, typically importing their inputs and exporting their output for final consumption in the U.S.[25] We interact the foreign ownership indicator with the *maquiladora* dummy to measure whether establishments of this type are disproportionately likely to domestically outsource employees (i.e., employ Mexican workers formally hired by a third party in Mexico) than other foreign-owned establishments. As expected, Column (6) shows that the share of outsourced employees in *maquiladora* establishments is 2 percentage points higher than that in other foreign-owned establishments (p=0.000).

[25] See Estefan (2023) for a thorough description of this program.

B.2 Revenue Growth and Outsourcing

Since outsourcing shifts the burden of legal battles against workers to the staffing shell company, outsourced employment may respond more flexibly than direct hiring to idiosyncratic shocks in establishment revenue. To examine the response of outsourcing to idiosyncratic revenue shocks, we regress outsourcing on revenue at the establishment level for three alternative outsourcing measures, along with establishment fixed effects and year dummies. The first measure of outsourcing is a dummy indicating that the establishment hires at least one worker through outsourcing, which captures outsourcing on the extensive margin; the second measure is the inverse sine transformation of the number of outsourced workers, which captures outsourcing on the intensive margin; and the third measure is the outsourced share of total employment, which captures the adjustment of outsourced employment relative to that of directly hired employment. Table B.2 reports results from this exercise. Across the three measures, we find that outsourcing is higher for establishments experiencing positive revenue shocks, supporting the hypothesis that outsourcing enables employing establishments to flexibly adjust their labor costs. On average, a 1 percent shock to revenue increases the probability of outsourcing on the extensive margin by 0.6 percentage points (p=0.000), the number of outsourced workers by 3.2 percent (p=0.000), and the outsourced employment share by 0.3 percentage points (p=0.000). These results echo findings for the U.S. showing that outsourced employment responds faster to idiosyncratic productivity shocks than directly hired employment (Atencio De Leon, 2023).

Table B.2: Outsourcing and Revenue Shocks at the Establishment Level

Regressor	$\mathbb{1}_{\{\text{Outsourced Workers}>0\}}$	IHS(Outsourced Workers)	Employment Share of Outsourcing
	(1)	(2)	(3)
Log(Total Revenue)	0.006***	0.032***	0.003***
	(0.001)	(0.003)	(0.0005)
N	226,784	226,784	226,784
R^2	0.02	0.006	0.004

Notes: All regressions include establishment fixed effects and time dummies. Standard errors are robust to heteroskedasticity of unknown form and are clustered at the establishment level. ***p<0.01.
Source: Authors' elaboration using data from the Mexican economic census waves from 1994 to 2019.

C Estimation Details

C.1 Measurement of Output and Productive Inputs

We measure output and productive inputs following, to the extent possible, the standard procedures used in the U.S. (see Syverson, 2004; Kehrig, 2015). The paragraphs below provide details about the construction of our output and input measures.

Output.- We construct a deflated measure of output for establishment i operating in industry j and period t, which captures the goods produced and sold in the same year and the produced goods stored in inventories, as follows:

$$Y_{it}^{j} = \frac{\text{Production}_{it}}{\text{Final Goods Price Deflator}_{t}^{j(i)}},$$

where $j(i)$ is a mapping from establishment to industry, Production_{it} is the value of the establishment's production, including the change in inventories from the beginning to the end of the calendar year, and $\text{Final Goods Price Deflator}_{t}^{j}$ is a price deflator for final goods at the 3-digit industry level from the Mexican producer price index, the *índice nacional de precios al productor* (INPP). The base period for this price index is July 2019. Since, for some industries, this price index is not available for years prior to 2010, we roll back the industry-specific price indexes using broad sector (i.e., primary, secondary, and tertiary) price index growth rates. We follow a similar procedure to impute price index values elsewhere in our estimation of productive inputs.

Labor and Wages.- To measure total labor input, we calculate the number of workers in the establishment. The census reports worker counts separately for four types of employment arrangements: remunerated insourced workers, nonpaid insourced workers, outsourced workers, and workers hired as contractors. Importantly, all worker counts include only workers hired to work on the establishment's premises, excluding those performing tasks not part of the establishment's economic activities, such as security, cleaning, and gardening. We compute the establishment's total worker count as follows:

$$L_{it} = \mathrm{L}_{it}^{\text{Insourced Paid}} + \mathrm{L}_{it}^{\text{Outsourced}} + \mathrm{L}_{it}^{\text{Contractors}},$$

where L_{it}^{j} denotes the number of workers in category j in establishment i and year t.

Our labor input measure excludes nonpaid insourced workers. Including these workers would lead to systemic bias in the estimated labor income shares, as labor compensation metrics in the census omit the labor income of the self-employed, counting it instead as capital income. The exclusion of nonpaid insourced workers from our labor input measure is essential because previous literature shows that rates of self-employment are greater in developing countries than in rich countries (e.g., Gollin, 2008). Since most nonpaid insourced workers are family members, the main caveat associated with excluding these workers is that our markdown measures do not account for labor exploitation among establishment owners and their family members.

Given our labor input definition, the labor compensation of establishment i in year t is

$$w_{it}L_{it} = \frac{\text{Total Workforce Compensation}_{it}}{\text{Intermediate Inputs Price Deflator}_{t}},$$

where $\text{Total Workforce Compensation}_{it}$ is the sum of the total labor compensation to remunerated insourced workers, outsourced workers, and workers hired as contractors, and the term $\text{Intermediate Inputs Price Deflator}_{t}$ denotes the price deflator for intermediate inputs at time t within the INPP.

Capital.- In the absence of reliable data on capital utilization rates for Mexico, we measure the capital stock as the unadjusted sum of all reported fixed assets owned by the establishment at the end of the period, which include buildings, machinery, vehicles, and computers. The capital stock of the establishment is therefore

$$K_{it} = \frac{\text{Fixed Assets Owned by the Establishment}_{it}}{\text{Capital Formation Price Deflator}_{t}},$$

where $\text{Capital Formation Price Deflator}_{t}$ is the INPP price deflator for capital at time t.

To measure capital expenditures, we simply multiply the capital stock by a rental rate of $r = 0.072$, which we obtain from Instituto Nacional de Estadística y Geografía (2022), as follows:

$$r_{it}K_{it} = \frac{\text{Fixed Assets Owned by the Establishment}_{it} \times 0.072}{\text{Capital Formation Price Deflator}_{t}}.$$

Materials and Energy.- Mexican data sources separately report raw materials used in production and resales. To construct our material input measure, we first exclude resales because, by definition, resales are products bought and then resold without any change to the product. Then, we deflate raw materials using the same price deflator that we use for intermediate inputs. Therefore, our materials input measure is

$$p_{it}^{M} M_{it} = \frac{\text{Raw Materials Used in Production}_{it}}{\text{Intermediate Inputs Price Deflator}_{t}}.$$

Finally, to construct our energy input measure, we add up the establishment's properly deflated usage of fuels for production and electricity consumption, as follows:

$$p_{it}^{E} E_{it} = \frac{\text{Fuels Used in Production}_{it}}{\text{Fuels Price Deflator}_{t}} + \frac{\text{Electricity Consumption}_{it}}{\text{Electricity Price Deflator}_{t}},$$

where $\text{Fuels Price Deflator}_{t}$ and $\text{Electricity Price Deflator}_{t}$ are the INPP fuel and electricity price deflators for period t, respectively.

Cost Shares.- The total cost of the establishment is calculated as

$$TC_{it} = w_{it} L_{it} + r_{it} K_{it} + p_{it}^{M} M_{it} + p_{it}^{E} E_{it}.$$

Hence, the input cost shares are calculated as

$$s_{it}^{L} = \frac{w_{it} L_{it}}{TC_{it}},$$

$$s_{it}^{K} = \frac{r_{it} K_{it}}{TC_{it}},$$

$$s_{it}^{M} = \frac{p_{it}^{M} M_{it}}{TC_{it}},$$

and

$$s_{it}^{E} = \frac{p_{it}^{E} E_{it}}{TC_{it}}.$$

Note that the ratio of any two cost shares is equal to the ratio of any two error-free revenue

shares (e.g., $\hat{\alpha}_{it}^{M}/\hat{\alpha}_{it}^{L} = s_{it}^{M}/s_{it}^{L}$).

C.2 Markdown Estimation Details

This section provides further details of our markdown estimation procedures. Section C.2.1 follows the standard cost minimization procedure to derive the formulas to construct markdowns using revenue elasticities and revenue shares. Section C.2.2 provides the details of the production function estimation.

C.2.1 Deriving an Expression for Markdowns

As described above, the wage markdown is identified by the ratio of the output elasticity of labor to its revenue share, divided by the establishment's markup. We begin our exposition by deriving the identifying equation for the establishment's markup and then show that the wage markdown is indeed identified as the ratio of the output elasticity of labor to its revenue share, divided by the markup.

We consider an active establishment i that produces output Q_{it} at time t and sells it in the market at a unitary price of P_{it}, using the production technology

$$Q_{it} = F(L_{it}, K_{it}, M_{it}, E_{it}; \Omega_{it}),$$

where L_{it}, K_{it}, M_{it}, E_{it}, and Ω_{it} denote labor, capital, materials, energy, and productivity, respectively. We assume that the production function F is continuous and twice differentiable with respect to its arguments. Furthermore, capital is assumed to be a predetermined input, meaning that it is chosen one period in advance, and a dynamic input, meaning that the optimal choice of capital depends on its previous values. On the other hand, the labor, materials, and energy used by the establishment are assumed to be flexible inputs, or inputs chosen each period by the establishment after it observes its productivity realization, and static inputs, which satisfy static first-order conditions. Additionally, the establishment is assumed to have some level of power in the final good market and the markets for labor and energy, allowing it to influence prices, but it is assumed that the establishment has no market power in the capital and raw materials markets. Finally, we assume that the establishment faces a downward-

sloping demand curve for its final good.

The establishment solves the following intratemporal cost minimization problem, conditional on its productivity realization and optimal output and capital choices:

$$\mathscr{C}(Q_{it}, K_{it}, w_{it}, r_{it}, p^M_{it}, p^E_{it}, \Omega_{it}) = \min_{\{L_{it}, M_{it}, E_{it}\}} w_{it}(L_{it})L_{it} + r_{it}K_{it} + p^M_{it}M_{it} + p^E_{it}(E_{it})E_{it}$$
$$\text{s.t. } Q_{it} = F(L_{it}, K_{it}, M_{it}, E_{it}; \Omega_{it}),$$

with the associated Lagrangian function

$$\mathscr{L}^{\min} = w_{it}(L_{it})L_{it} + r_{it}K_{it} + p^M_{it}M_{it} + p^E_{it}(E_{it})E_{it} + \lambda_{it}(Q_{it} - F(L_{it}, K_{it}, M_{it}, E_{it}; \Omega_{it})),$$

where w_{it}, r_{it}, p^M_{it}, and p^E_{it} denote the establishment's price for labor, capital, materials, and energy, respectively.

The first-order conditions of this cost minimization problem offer crucial insights for the identification of the establishment's markup, defined as the ratio of output price to marginal cost, or $\mu_{it} \equiv \frac{P_{it}}{\frac{\partial \mathscr{C}(Q_{it}, K_{it}, w_{it}, r_{it}, p^M_{it}, p^E_{it}, \Omega_{it})}{\partial Q_{it}}}$.[26] First, by the envelope theorem, we have that the Lagrangian multiplier is the marginal cost of production, or $\lambda_{it} = \frac{\partial \mathscr{C}(Q_{it}, K_{it}, w_{it}, r_{it}, p^M_{it}, p^E_{it}, \Omega_{it})}{\partial Q_{it}}$. Second, the first-order condition for raw materials is

$$\frac{\partial \mathscr{L}^{\min}}{\partial M_{it}} = p^M_{it} - \lambda_{it}\frac{\partial F(L_{it}, K_{it}, M_{it}, E_{it}; \Omega_{it})}{\partial M_{it}} = 0.$$

Rearranging terms in the last equality, multiplying both sides of the equation by $\frac{M_{it}}{Q_{it}}$, substituting the marginal cost of production for λ_{it}, and using the markup definition, we find that the markup of establishment i is identified by the ratio on the right-hand side of the following equation:

$$\mu_{it} = \frac{\theta^M_{it}}{\alpha^M_{it}}, \tag{4}$$

where $\theta^M_{it} \equiv \frac{\partial \log F()}{\partial \log M_{it}}$ is the output elasticity with respect to raw materials and $\alpha^M_{it} \equiv \frac{p^M_{it}M_{it}}{P_{it}Q_{it}}$ is its

[26] The ratio on the right-hand side of the equation is equal to 1 only when there is perfect competition and the establishment has no influence over the market price of output, and it is greater than 1 whenever there is imperfect competition and the establishment has price-setting power.

revenue share.

We then derive an equation that identifies the wage markdown, defined as the ratio of the marginal revenue product of labor to the wage rate, or $v_{it} \equiv \frac{\frac{\partial P_{it}Q_{it}}{\partial L_{it}}}{w_{it}}$.[27] The first-order condition of the cost minimization problem with respect to labor is

$$\frac{\partial \mathscr{L}^{\min}}{\partial L_{it}} = w'_{it}(L_{it})L_{it} + w_{it}(L_{it}) - \lambda_{it}\frac{\partial F(L_{it}, K_{it}, M_{it}, E_{it}; \Omega_{it})}{\partial L_{it}} = 0.$$

Rearranging terms, multiplying both sides of the equation by $\frac{L_{it}}{Q_{it}}$, and substituting the labor supply elasticity definition $\varepsilon_{L,w} \equiv \frac{\partial \log L_{it}}{\partial \log w_{it}}$ into the resulting equation, we obtain

$$\left(1 + \frac{1}{\varepsilon_{it}^{L,w}}\right) = \frac{\frac{\theta_{it}^{L}}{\alpha_{it}^{L}}}{\mu_{it}}. \tag{5}$$

Thus, a sufficient condition for the desired result to hold is the equality of the establishment's wage markdown and the reciprocal of the labor supply elasticity. If the establishment is profit maximizing, this condition holds. To see why, consider the profit maximization problem of the establishment:

$$\Pi(w_{it}, r_{it}, p_{it}^{M}, p_{it}^{E}, \omega_{it}) = \max_{\{L_{it}, M_{it}, E_{it}\}} P_{it}Q_{it} - w_{it}(L_{it})L_{it} - r_{it}K_{it} - p_{it}^{M}M_{it} - p_{it}^{E}(E_{it})E_{it}$$
$$\text{s.t.} \quad Q_{it} = F(L_{it}, K_{it}, M_{it}, E_{it}; \Omega_{it}).$$

Since labor is assumed to be a flexible input, we have that the first-order condition of the profit maximization problem depends only on labor at t. Specifically, we have

$$\frac{\partial \mathscr{L}^{\max}}{\partial L_{it}} = \frac{\partial P_{it}Q_{it}}{\partial L_{it}} - w'_{it}(L_{it})L_{it} - w_{it}(L_{it}) = 0,$$

where $\mathscr{L}^{\max}$ is the Lagrangian associated with the dynamic profit maximization problem.

Rearranging terms and substituting the definition of the labor supply elasticity into the re-

[27] The ratio on the right-hand side of the equation is equal to 1 when the marginal worker is paid exactly her marginal contribution to the revenues of the establishment, and it is greater than 1 when the wage rate is less than her marginal contribution to the establishment's revenues. Put differently, the reciprocal of the markdown is the fraction of the revenues generated by the marginal worker for which she is effectively paid.

sulting equation, we obtain

$$\frac{\frac{\partial P_{it}Q_{it}}{\partial L_{it}}}{w_{it}} = \left(1 + \frac{1}{\varepsilon^L_{it}}\right) = \upsilon_{it}, \tag{6}$$

where the last equality follows from the markdown definition.

Substituting the last equality in Equation (6) into Equation (5), we finally obtain

$$\upsilon_{it} = \frac{\frac{\theta^L_{it}}{\alpha^L_{it}}}{\mu_{it}}. \tag{7}$$

The right-hand side of this equation identifies the labor markdown, as Equation (4) identifies the markup of the establishment. The wage markdown of the establishment can therefore be estimated as a ratio of ratios: the ratio of (1) the ratio of the output elasticity of labor to its revenue share to (2) the ratio of the output elasticity of raw materials to their revenue share.

C.2.2 Production Function Estimation

The estimation of production functions is one of the oldest problems in econometrics. The key challenge for their empirical estimation is that firms optimally choose their inputs as a function of their productivity, which is unobservable to the econometrician. This simultaneity problem has been called *transmission bias* in the industrial organization literature, dating back to Marschak and Andrews (1944). As ignoring this source of endogeneity could lead to severe overestimation of output elasticities for flexible inputs relative to predetermined inputs, sophisticated methods have been devised to address this issue in the estimation of production functions. These include dynamic panel methods (Blundell and Bond, 2000), which propose using lagged first-differences and lagged levels of productive inputs as instruments for production function equations in levels, and "proxy" methods (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Wooldridge, 2009; Ackerberg, Caves and Frazer, 2015), which assume the existence of a flexible input with invertible demand in terms of productivity to "control" for productivity. These methods are particularly suitable in our context and will serve in the estimation of establishment-level markdowns.

We assume that logged output satisfies $y_{it} = \log(Q_{it}) + \varepsilon_{it}$, where ε_{it} denotes measurement error that enters the production estimate in a multiplicative fashion and satisfies $E[\varepsilon_{it}|Q_{it}] = 0$.

This measurement error is assumed to be unobservable for the establishment. Furthermore, we assume that productivity is multiplicative in production, or $Q_{it} = \Omega_{it} F(L_{it}, K_{it}, M_{it}, E_{it})$.

Therefore, we can write

$$y_{it} = f(l_{it}, k_{it}, m_{it}, e_{it}) + \omega_{it} + \varepsilon_{it}, \tag{8}$$

where $f(l_{it}, k_{it}, m_{it}, e_{it}) = \log(F(L_{it}, K_{it}, M_{it}, E_{it}))$ and l_{it}, k_{it}, m_{it}, e_{it}, and ω_{it} denote the log transformations of labor, capital, materials, energy, and productivity, respectively.

Crucially, productivity ω_{it} is observed by the establishment before it chooses its flexible inputs, but it is not observable to the econometrician. The so-called proxy method deals with this source of endogeneity by first assuming that the establishment's demand for raw materials is an invertible function of the period's productivity realization, or $m_{it} = m_t(\omega_{it}; l_{it}, k_{it}, e_{it})$. Under this assumption, there exists some function $h_t(; k_{it}, l_{it}, e_{it}) = m_t^{-1}(; k_{it}, l_{it}, e_{it})$ such that $\omega_{it} = h_t(m_{it}; k_{it}, l_{it}, e_{it})$.

This assumption is then supplemented with another assumption regarding the stochastic process that governs productivity. For our application, we assume that productivity ω_{it} is a Markovian stochastic process with a conditional expectation function denoted by $E[\omega_{it}|\omega_{i,t-1}] = g_t(\omega_{i,t-1})$, so we have

$$\omega_{it} = g_t(\omega_{i,t-1}) + \zeta_{it}, \tag{9}$$

where ζ_{it} is period t's productivity innovation, satisfying $E[\zeta_{it}|\omega_{i,t-1}] = 0$.

Substituting Equation (9) into Equation (8), we have

$$y_{it} = f(l_{it}, k_{it}, m_{it}, e_{it}) + g_t(\omega_{i,t-1}) + \zeta_{it} + \varepsilon_{it}. \tag{10}$$

Note that, by Equation (9), $\omega_{i,t-1}$ is mean independent from period t's input choices, so the only problematic source of endogeneity in the estimation of f in Equation (10) is the productivity innovation ζ_{it}. However, the timing assumptions made regarding the input choices by the establishment provide a natural instrumental variable (IV) strategy to circumvent this estimation hurdle. Namely, all flexible input choices from period $t-1$, the capital input choice in

period t, their interactions, and their squares are mean independent from ζ_{it} by construction, or:

$$E[\zeta_{it} \times \mathbf{Z}_{it}] = \mathbf{0}, \tag{11}$$

where $\mathbf{Z}_{it}$ contains all the elements in $(l_{i,t-1}, k_{it}, m_{i,t-1}, e_{i,t-1})$, their two-way interactions, and their squares.

The moments in Equation (11) identify the production function parameters provided that the functional dependence of f on the productive input vector can be summarized with a sufficiently small number of parameters, and provided that the candidate instruments meet the so-called relevance condition. This condition requires that the establishment's input choices are auto-correlated. A sufficient condition for this assumption to hold is for input prices to be persistent over time.

Having laid out the theoretical framework for identification, we describe in detail our three-stage estimation procedure, which follows directly from Ackerberg, Caves and Frazer (2015). For specificity, we assume that the production function is translog and can be reasonably approximated using a quadratic polynomial in $(l_{it}, k_{it}, m_{it}, e_{it})$ with a coefficient vector $\boldsymbol{\beta}$.

The first step in the estimation procedure leverages the fact that output can be written as a function of observables and measurement error, as follows:

$$\begin{aligned} y_{it} &= f(l_{it}, k_{it}, m_{it}, e_{it}; \boldsymbol{\beta}) + h_t(m_{it}; k_{it}, l_{it}, e_{it}) + \varepsilon_{it} \\ &= \phi_t(l_{it}, k_{it}, m_{it}, e_{it}) + \varepsilon_{it}, \end{aligned}$$

where $\phi_t(l_{it}, k_{it}, m_{it}, e_{it}) \equiv f(l_{it}, k_{it}, m_{it}, e_{it}; \boldsymbol{\beta}) + h_t(m_{it}; k_{it}, l_{it}, e_{it})$. We can estimate ϕ_t using a third-degree polynomial in $(l_{it}, k_{it}, m_{it}, e_{it})$. Let $\hat{\phi}_t$ denote the OLS estimate of ϕ_t.

In the second step, for a hypothetical guess of $\boldsymbol{\beta}$, we construct estimates of ω_{it}, as follows:

$$\hat{\omega}_{it}(\boldsymbol{\beta}) = \hat{\phi}_t(l_{it}, k_{it}, m_{it}, e_{it}) - \mathbf{X}'_{it}\boldsymbol{\beta},$$

where $\mathbf{X}_{it}$ is a vector containing the terms of the quadratic polynomial in $(l_{it}, k_{it}, m_{it}, e_{it})$. Then, we regress $\hat{\omega}_{it}(\boldsymbol{\beta})$ on a cubic polynomial in $\hat{\omega}_{i,t-1}(\boldsymbol{\beta})$. The residuals from this regression are the implied values of ζ_{it}, denoted as $\hat{\zeta}_{it}(\boldsymbol{\beta})$.

In the final step, we then search over the $\boldsymbol{\beta}$ space using standard generalized method of moments (GMM) techniques to minimize the following moment conditions:

$$E\left[\zeta_{it}(\boldsymbol{\beta}) \times \mathbf{Z}_{it}\right] = 0. \tag{12}$$

Our estimate of $\boldsymbol{\rho}$ is given by the coefficient estimate of an OLS regression of $\hat{\omega}_{it}(\boldsymbol{\beta})$ on a third-order polynomial of $\hat{\omega}_{it}(\boldsymbol{\beta})$, evaluated at the parameter vector estimate $\boldsymbol{\beta}$ that solves the GMM minimization problem.

C.2.3 Markdown Estimation

The GMM estimator of the parameter vector $\boldsymbol{\beta}$, denoted by $\hat{\boldsymbol{\beta}}$, allows us to calculate the output elasticities with respect to raw materials and labor. If we assume that the production function is Cobb–Douglas, output elasticities are constant and are given by

$$\hat{\theta}^m_{it} = \hat{\beta}_m \text{ and } \hat{\theta}^l_{it} = \hat{\beta}_l.$$

Thus, assuming a Cobb–Douglas production function amounts to assuming that output elasticities do not vary across establishments within the same industry, thereby implying that markdown trajectories within an industry mirror those of the ratios of the expenditure share of raw materials to the expenditure share of labor.

In contrast, under our baseline assumption that the production function is translog, output elasticities depend on the establishment's input choices and are given by

$$\hat{\theta}^m_{it} = \hat{\beta}_m + 2\hat{\beta}_{mm} + \hat{\beta}_{mk}k_{it} + \hat{\beta}_{me}e_{it} + \hat{\beta}_{ml}l_{it} \text{ and}$$

$$\hat{\theta}^l_{it} = \hat{\beta}_l + 2\hat{\beta}_{ll} + \hat{\beta}_{lk}k_{it} + \hat{\beta}_{lm}m_{it} + \hat{\beta}_{le}e_{it}.$$

Finally, we compute revenue shares of raw materials and labor. As in de Loecker and Warzynski (2012), we use the estimated residual from the first step in our estimation procedure, denoted by $\hat{\varepsilon}_{it}$, to correct these shares for measurement error in the revenue measure. Specifically, since we observe only $Y_{it} \equiv Q_{it}\exp(\varepsilon_{it})$, we compute the error-free expenditure

shares $\hat{\alpha}^M_{it} = \frac{p^M_{it} M_{it}}{P_{it} \frac{Y_{it}}{\exp\{\hat{\varepsilon}_{it}\}}}$ and $\hat{\alpha}^L_{it} = \frac{w_{it} L_{it}}{P_{it} \frac{Y_{it}}{\exp\{\hat{\varepsilon}_{it}\}}}$ for raw materials and labor, respectively. This correction isolates the revenue variation that correlates with the productive inputs $(l_{it}, m_{it}, k_{it}, e_{it})$ and removes all other sources of variation in revenues.

C.3 Robustness Checks and Alternative Estimation Approaches

We conduct two checks to verify the robustness of our estimates. First, Gandhi, Navarro and Rivers (2020) show that the moment conditions implied by the choice of instruments in the "proxy" method are insufficient for the identification of $\boldsymbol{\beta}$. This identification problem amounts to our having insufficient information about the shape of the production function in the moment conditions implied by our IV strategy. To resolve this issue, we reestimate the markdowns assuming constant returns to scale, as suggested in (Flynn, Traina and Gandhi, 2019). Thus, in addition to the moment conditions in Equation (11), we add a constant-returns-to-scale assumption,[28] which implies the following moment condition:

$$E\left[\sum_{I\in\{l,k,m,e\}} \frac{\partial f(l_{it}, k_{it}, m_{it}, e_{it})}{\partial I_{it}}\right] - 1 = 0. \tag{13}$$

Second, Bond et al. (2021) highlights additional identification and estimation issues pertaining to the ratio estimator of the markup, which arise when the econometrician uses the revenue elasticity for a flexible input in place of its output elasticity, as in our case. In particular, if the establishment maximizes profits and minimizes production costs, the markup ratio estimator that relies on the revenue elasticity of the flexible input equals one and thus is uninformative about actual markups.[29] While the ratio estimator for markdowns is immune to this criticism, as a robustness check, we follow the recommendation in Bond et al. (2021) and use the differences in revenue shares between groups of establishments within the same industry to infer how markdowns differ across groups.

For simplicity, we assume that all establishments within an industry have the same Cobb–Douglas production function. Taking logs in Equation (7), we have $\log v_{it} = \log\theta^L_{it} - \log\alpha^L_{it} - \mu_{it}$.

[28] This assumption seems to be a good approximation for the U.S. manufacturing sector (Basu and Fernald, 1997; Foster, Haltiwanger and Syverson, 2008; Syverson, 2004).

[29] See Appendix C.4 for a proof of this and the following statement.

Substituting Equation (4) into this equation and rearranging terms, we have

$$\log\left(\frac{\alpha_{it}^M}{\alpha_{it}^L}\right) = \log\left(\frac{\beta^M}{\beta^L}\right) + \log v_{it}, \tag{14}$$

where the input elasticities $\beta^M = \theta_{it}^M$ and $\beta^L = \theta_{it}^L$ are constant terms.

To study whether a binary characteristic of the establishment D_{it} impacts markdowns, we can specify a linear relationship between log markdowns and this characteristic, as follows:

$$\log v_{it} = \delta_0 + D_{it}\delta_1 + \eta_{it}, \tag{15}$$

where $E[\eta_{it}|D_{it}] = 0$.

Substituting Equation (14) into Equation (15), we have the linear specification

$$\log\left(\frac{\alpha_{it}^M}{\alpha_{it}^L}\right) = \delta_0 + \log\left(\frac{\beta^M}{\beta^L}\right) + D_{it}\delta_1 + \eta_{it}. \tag{16}$$

From this equation, we can learn about the association between log markdowns and the binary variable D_{it}. Thus, we estimate Equation (16) via OLS for each characteristic of interest.

C.4 Proofs

C.4.1 Proof: The Ratio Estimator of the Markup Equals 1

This result follows because, if a establishment with market power in the final good market maximizes profits, it internalizes the effect of its output choices on prices, so the markup equals one plus the reciprocal of the price elasticity of demand. Specifically, the ratio of the marginal

revenue of raw materials, denoted by $\theta_{it}^{M,\text{revenues}}$, to their revenue share is

$$\begin{aligned}
\frac{\theta_{it}^{M,\text{revenue}}}{\alpha_{it}^{M}} &= \frac{\frac{\partial p_{it}(Q_{it})Q_{it}}{\partial M_{it}}\frac{M_{it}}{p_{it}(Q_{it})Q_{it}}}{\alpha_{it}^{M}} \\
&= \frac{\left(\frac{\partial p_{it}(Q_{it})}{\partial Q_{it}}\frac{\partial Q_{it}}{\partial M_{it}}Q_{it} + \frac{\partial Q_{it}}{\partial M_{it}}P_{it}(Q_{it})\right)\frac{M_{it}}{P_{it}(Q_{it})Q_{it}}}{\alpha_{it}^{M}} \\
&= \frac{\theta_{it}^{M,\text{output}} \times \left(1 + \frac{1}{\epsilon_{it}^{P,Q}}\right)}{\alpha_{it}^{M}} \\
&= \mu_{it}\left(1 + \frac{1}{\epsilon_{it}^{P,Q}}\right) \\
&= 1,
\end{aligned}$$

where $\theta_{it}^{M,\text{output}}$ is the output elasticity of raw materials and $\epsilon_{it}^{P,Q}$ is the price elasticity of demand. The last equality above follows from Lerner's monopoly pricing rule.

C.4.2 Proof: The Ratio Estimator of the Markdown Recovers Actual Markdowns

Fortunately, the ratio estimator for markdowns is immune to the criticism of Bond et al. (2021) because markdowns are estimated as a ratio of ratios. By a line of reasoning analogous to that for markups, we have that our markdown measure satisfies the following:

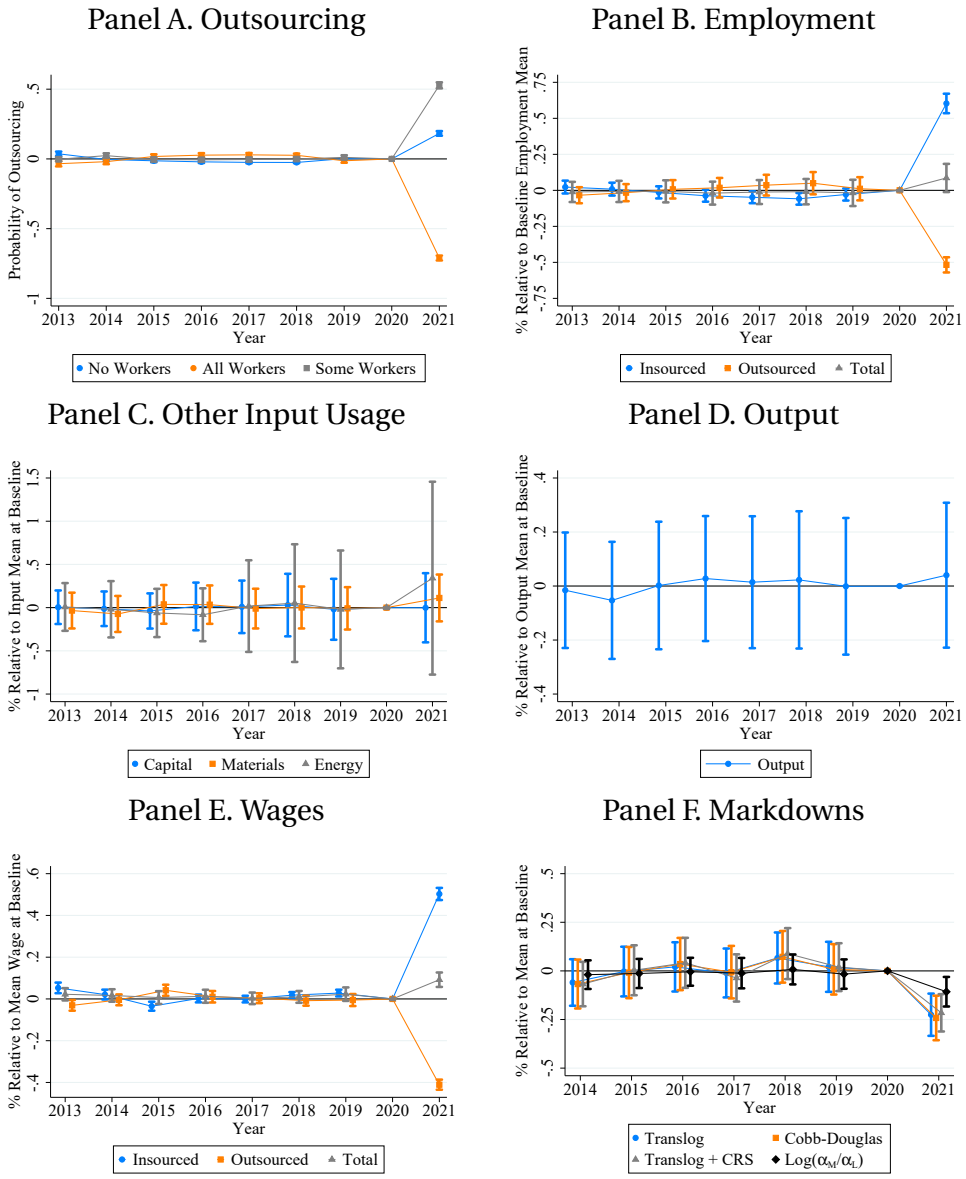
$$\frac{\frac{\theta_{it}^{L,\text{revenue}}}{\alpha_{it}^{L}}}{\frac{\theta_{it}^{M,\text{revenue}}}{\alpha_{it}^{M}}} = \frac{\frac{\theta_{it}^{L,\text{output}}\left(1+\frac{1}{\epsilon_{it}^{P,Q}}\right)}{\alpha_{it}^{L}}}{\mu_{it}\left(1+\frac{1}{\epsilon_{it}^{P,Q}}\right)} = \upsilon_{it},$$

where the last equality follows from Equation (7).

D Robustness Checks

D.1 Impact Estimates under Reform Anticipation Effects

Figure D.1: Anticipation Effects – Testing for Pretrends in Annual Outcomes



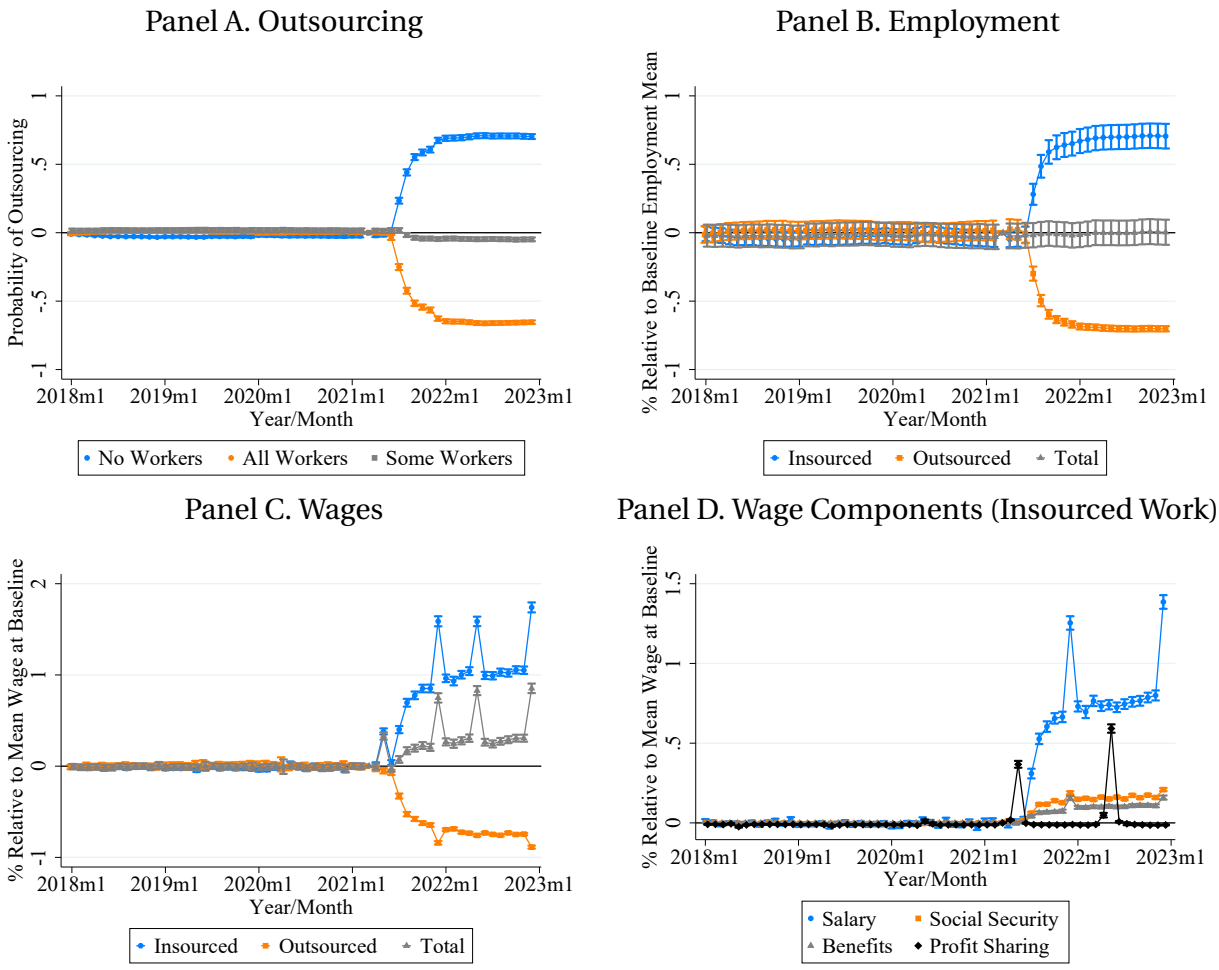
Notes: Each panel in this figure presents the regression coefficients and 95 percent confidence intervals of year dummies interacted with the outsourced employment share of the establishment in 2018, controlling for year and the outsourced employment share in 2018. Standard errors are robust to heteroskedasticity of unknown form and are clustered at the establishment level. The interaction for 2020 is excluded from each regression, so the effects can be interpreted as deviations from the outcome mean in 2020 of the group with zero exposure in 2018. All monetary amounts are deflated to July 2019 with Mexico's GDP deflator, the *índice nacional de precios al productor* (INPP), and its subindexes.
Source: Authors' elaboration using data from the Mexican annual manufacturing survey from 2013 to 2021.

Table D.1: Anticipation Effects – Causal Impacts of the Reform on Annual Outcomes

		Panel A. Outsourcing		
Regressor	All Workers	Some Workers	No Workers	
	(1)	(2)	(3)	
$\text{Outsourcing}_{i,2018} \times \text{Post}_t$	-0.71***	0.53***	0.18***	
	(0.01)	(0.01)	(0.01)	
N	85,152	85,152	85,152	
R^2	0.229	0.055	0.01	
		Panel B. Employment		
Regressor	Insourced	Outsourced	Total	
	(4)	(5)	(6)	
$\text{Outsourcing}_{i,2018} \times \text{Post}_t$	0.60***	-0.52***	0.09*	
	(0.03)	(0.03)	(0.05)	
N	85,152	85,152	85,152	
R^2	0.003	0.01	0.00005	
		Panel C. Usage of Other Inputs and Output		
Regressor	Capital Stock	Raw Materials	Energy	Output
	(7)	(8)	(9)	(10)
$\text{Outsourcing}_{i,2018} \times \text{Post}_t$	-0.001	0.11	0.34	0.04
	(0.20)	(0.14)	(0.57)	(0.14)
N	85,152	85,152	85,152	85,152
R^2	0.000002	0.000009	0.00005	0.000003
		Panel D. Wages		
Regressor	Total Pay/Total Workers	Insourced Pay/Total Workers	Outsourced Pay/Total Workers	
	(11)	(12)	(13)	
$\text{Outsourcing}_{i,2018} \times \text{Post}_t$	0.09***	0.50***	-0.41***	
	(0.02)	(0.01)	(0.01)	
N	85,152	85,152	85,152	
R^2	0.0004	0.013	0.039	
		Panel E. Markdowns		
Regressor	Translog	Cobb-Douglas	Translog+CRS	$\text{Log}(\frac{\alpha_M}{\alpha_L})$
	(14)	(15)	(16)	(17)
$\text{Outsourcing}_{i,2018} \times \text{Post}_t$	-0.23***	-0.24***	-0.22***	-0.11***
	(0.06)	(0.06)	(0.05)	(0.04)
N	20,065	20,065	20,065	20,065
R^2	0.001	0.001	0.001	0.0004

Notes: The effects shown correspond to impacts 1 year after the reform. The measure of cross-sectional exposure to the reform is the share of outsourced workers in 2018. All monetary amounts are deflated to July 2019 with Mexico's GDP deflator, the *índice nacional de precios al productor* (INPP), and its subindexes. Standard errors are robust to heteroskedasticity of unknown form and are clustered at the establishment level. The effects in Panel B are expressed relative to the mean employment level across all establishments in 2020, the year prior to the reform. The effects in Panel C are expressed relative to each outcome variable's mean in the year prior to the reform. The effects in Panel D are expressed relative to the mean total wage compensation across all establishments in the year prior to the reform. The estimation sample in Panel E includes only observations for which a lag of the input variables is available. * p<0.1, ***p<0.01.
Source: Authors' elaboration using data from the Mexican annual manufacturing survey from 2013 to 2021.

Figure D.2: Anticipation Effects – Testing for Pretrends in Monthly Outcomes



Notes: This figure presents the regression coefficients and 95 percent confidence intervals of date dummies interacted with the share of workers hired through outsourcing by the establishment at June 2018, controlling for date dummies and the share of outsourced workers in June 2018. Each panel presents results for a different set of outcomes. The effects in Panel B are expressed relative to the mean employment level across all establishments in the year prior to the reform (i.e., March 2020–March 2021). The effects in Panels C and D are expressed relative to the mean total wage compensation across all establishments in the year prior to the reform. Standard errors are robust to heteroskedasticity of unknown form and are clustered at the establishment level. The interaction for March 2021 is excluded from each regression, so the effects can be interpreted as deviations from the outcome mean of the comparison group in the month prior to the 2021 reform.
Source: Authors' elaboration using data from the Mexican monthly manufacturing survey from 2018 to 2023.

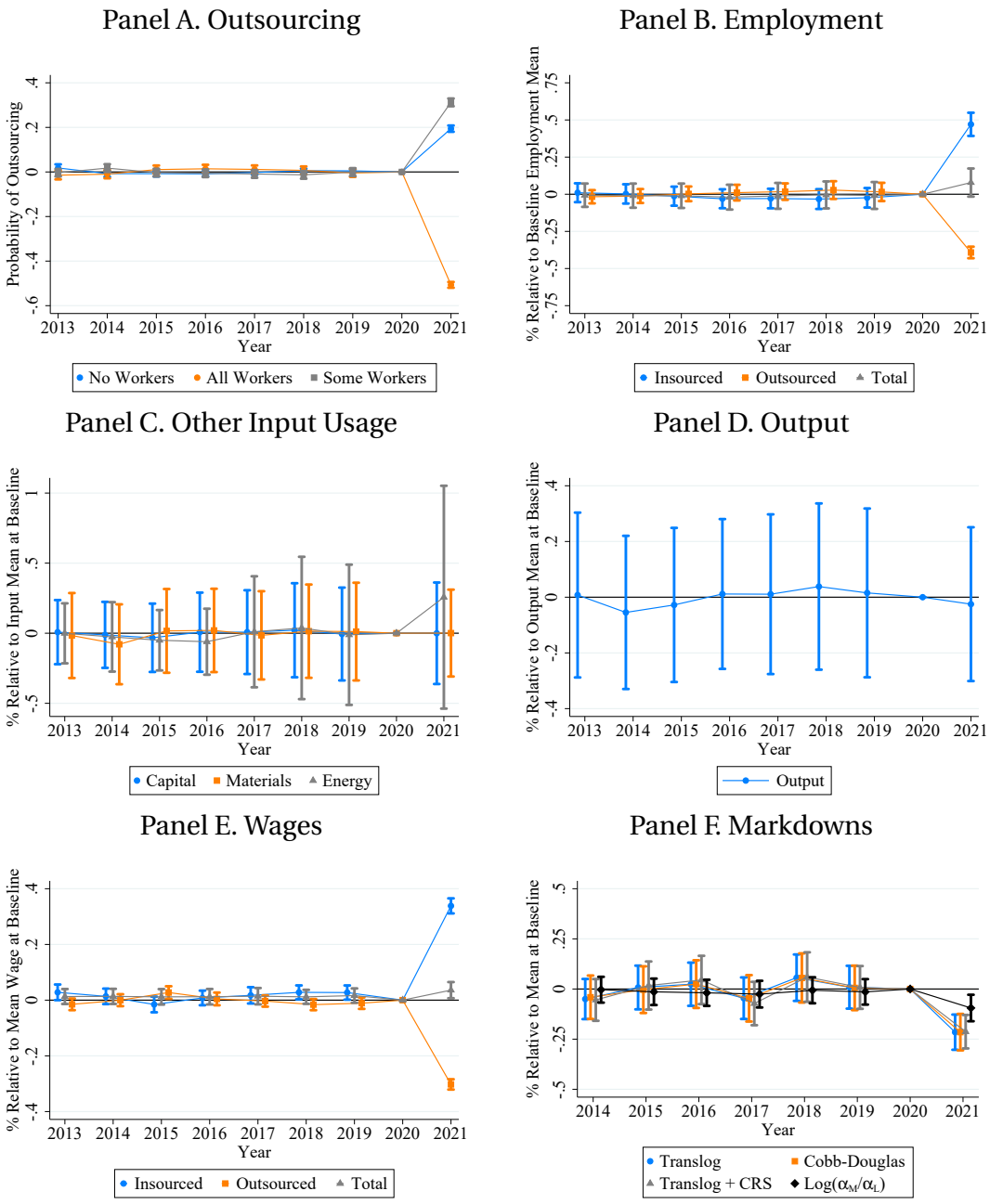
Table D.2: Anticipation Effects – Causal Impacts of the Reform on Monthly Outcomes

		Panel A. Outsourcing	
Regressor	All Workers	Some Workers	No Workers
	(1)	(2)	(3)
$\text{Outsourcing}_{i,\text{June 2018}} \times \text{Post}_t$	-0.65***	-0.05***	0.70***
	(0.01)	(0.01)	(0.01)
N	580,701	580,701	580,701
R^2	0.373	0.002	0.252
		Panel B. Employment	
Regressor	Insourced	Outsourced	Total
	(4)	(5)	(6)
$\text{Outsourcing}_{i,\text{June 2018}} \times \text{Post}_t$	0.70***	-0.70***	-0.0009
	(0.05)	(0.01)	(0.05)
N	580,701	580,701	580,701
R^2	0.005	0.06	0.00001
		Panel C. Wages	
Regressor	Insourced Pay/Total Workers	Outsourced Pay/Total Workers	Total Pay/Total Workers
	(7)	(8)	(9)
$\text{Outsourcing}_{i,\text{June 2018}} \times \text{Post}_t$	1.06***	-0.75***	0.31***
	(0.02)	(0.01)	(0.02)
N	580,701	580,701	580,701
R^2	0.087	0.227	0.011
		Panel D. Insourced Wage Components	
	Salaries	Social Security and Benefits	Profit Sharing
	(10)	(11)	(12)
$\text{Outsourcing}_{i,\text{June 2018}} \times \text{Post}_t$	0.73***	0.26***	0.59***
	(0.02)	(0.01)	(0.01)
N	580,701	580,701	580,701
R^2	0.104	0.075	0.01

Notes: The effects shown correspond to impacts 12 months after the reform. The measure of cross-sectional exposure to the reform is the share of outsourced workers in June 2018. The effects in Panel B are expressed relative to the mean employment level across all establishments in the year prior to the reform (i.e., March 2020–March 2021). The effects in Panels C and D are expressed relative to the mean total wage compensation across all establishments in the year prior to the reform. All monetary amounts are deflated with Mexico's GDP deflator, the *índice nacional de precios al productor* (INPP), and its subindexes. Standard errors are robust to heteroskedasticity of unknown form and are clustered at the establishment level. ***p<0.01.
Source: Authors' elaboration using data from the Mexican monthly manufacturing survey from 2018 to 2023.

D.2 Differences-in-Differences with a Dichotomous Treatment

Figure D.3: Dichotomous Treatment – Testing for Pretrends in Annual Outcomes



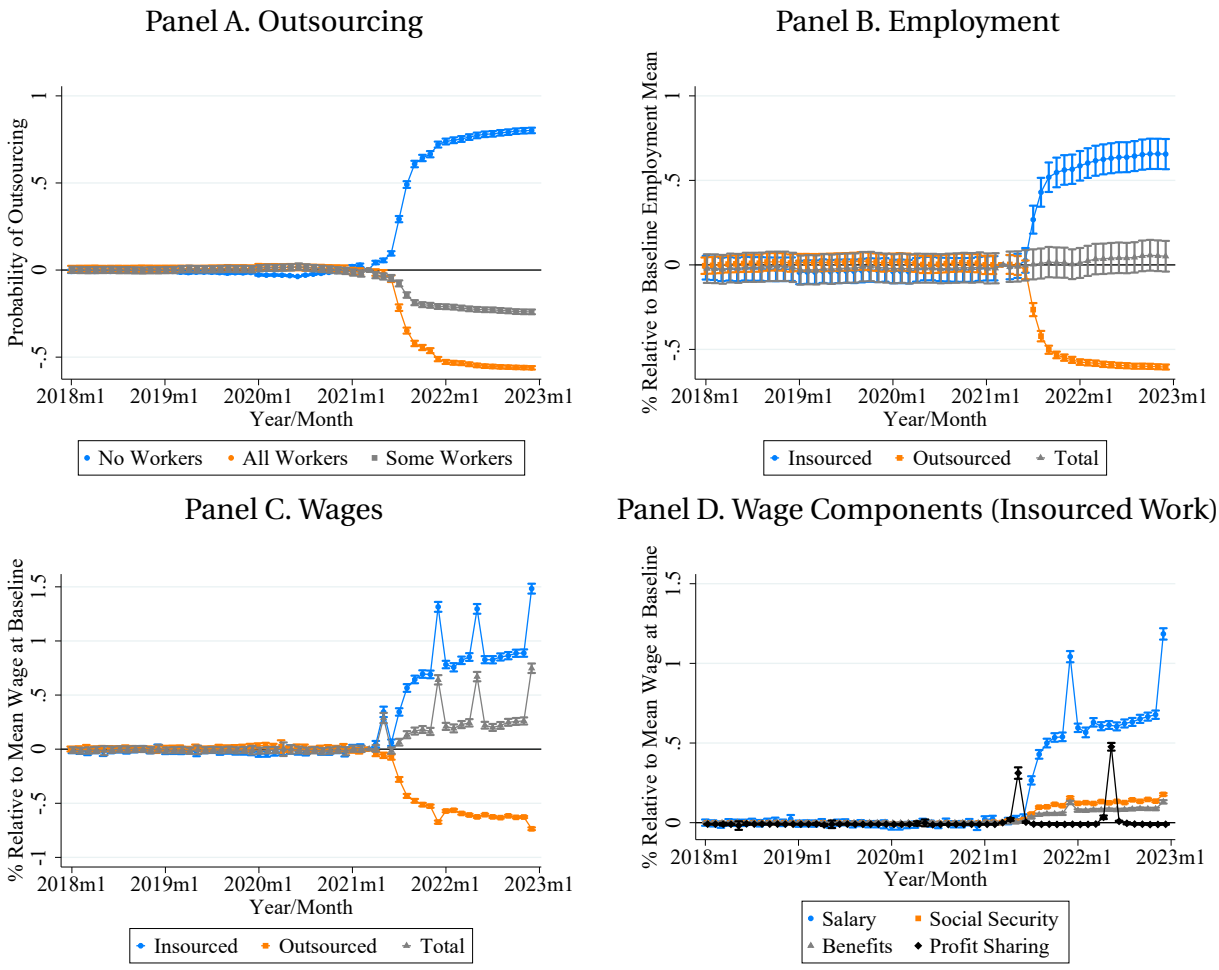
Notes: Each panel in this figure presents the regression coefficients and 95 percent confidence intervals of year dummies interacted with an indicator for the event of the establishment's outsourced employment share in 2020 being above the cross-sectional median of that year, controlling for year dummies and the same indicator. Standard errors are robust to heteroskedasticity of unknown form and are clustered at the establishment level. The interaction for 2020 is excluded from each regression, so the effects can be interpreted as deviations from the outcome mean of the group with zero exposure in the year prior to the 2021 reform. All monetary amounts are deflated to July 2019 with Mexico's GDP deflator, the *índice nacional de precios al productor* (INPP), and its subindexes.
Source: Authors' elaboration using data from the Mexican annual manufacturing survey from 2013 to 2021.

Table D.3: Dichotomous Treatment – Causal Impacts of the Reform on Annual Outcomes

		Panel A. Outsourcing		
Regressor	All Workers	Some Workers	No Workers	
	(1)	(2)	(3)	
Outsourcing$_{i,2020}$ × Post$_t$	-0.51***	0.31***	0.19***	
	(0.01)	(0.01)	(0.01)	
N	82,873	82,873	82,873	
R^2	0.096	0.034	0.021	
		Panel B. Employment		
Regressor	Insourced	Outsourced	Total	
	(4)	(5)	(6)	
Outsourcing$_{i,2020}$ × Post$_t$	0.47***	-0.39***	0.08	
	(0.04)	(0.02)	(0.05)	
N	82,873	82,873	82,873	
R^2	0.002	0.007	0.00006	
		Panel C. Usage of Other Inputs and Output		
Regressor	Capital Stock	Raw Materials	Energy	Output
	(7)	(8)	(9)	(10)
Outsourcing$_{i,2020}$ × Post$_t$	-0.0003	0.001	0.26	-0.02
	(0.18)	(0.16)	(0.41)	(0.14)
N	82,873	82,873	82,873	82,873
R^2	0.000002	0.000004	0.00004	0.000004
		Panel D. Wages		
Regressor	Total Pay/Total Workers	Insourced Pay/Total Workers	Outsourced Pay/Total Workers	
	(11)	(12)	(13)	
Outsourcing$_{i,2020}$ × Post$_t$	0.04**	0.34***	-0.30***	
	(0.01)	(0.01)	(0.01)	
N	82,873	82,873	82,873	
R^2	0.008	0.024	0.0001	
		Panel E. Markdowns		
Regressor	Translog	Cobb-Douglas	Translog+CRS	Log($\frac{\alpha_M}{\alpha_L}$)
	(14)	(15)	(16)	(17)
Outsourcing$_{i,2020}$ × Post$_t$	-0.22***	-0.21***	-0.21***	-0.09***
	(0.04)	(0.05)	(0.04)	(0.03)
N	19,167	19,167	19,167	19,167
R^2	0.002	0.002	0.002	0.0005

Notes: The effects shown correspond to impacts 1 year after the reform. The measure of cross-sectional exposure to the reform is an indicator for the event of the establishment's outsourced employment share in 2020 being above the cross-sectional median of that year. All monetary amounts are deflated to July 2019 with Mexico's GDP deflator, the *índice nacional de precios al productor* (INPP), and its subindexes. Standard errors are robust to heteroskedasticity of unknown form and are clustered at the establishment level. The effects in Panel B are expressed relative to the mean employment level across all establishments in 2020, the year prior to the reform. The effects in Panel C are expressed relative to each outcome variable's mean in the year prior to the reform. The effects in Panel D are expressed relative to the mean total wage compensation across all establishments in the year prior to the reform. The estimation sample in Panel E includes only observations for which a lag of the input variables is available. ** p<0.05, ***p<0.01.
Source: Authors' elaboration using data from the Mexican annual manufacturing survey from 2013 to 2021.

Figure D.4: Dichotomous Treatment – Testing for Pretrends for Monthly Outcomes



Notes: This figure presents the regression coefficients and 95 percent confidence intervals of date dummies interacted with an indicator for the event of the establishment's outsourced employment share in June 2020 being above the cross-sectional median of that month, controlling for date dummies and the same indicator. Each panel presents results for a different set of outcomes. The effects in Panel B are expressed relative to the mean employment level across all establishments in the year prior to the reform (i.e., March 2020–March 2021). The effects in Panels C and D are expressed relative to the mean total wage compensation across all establishments in the year prior to the reform. Standard errors are robust to heteroskedasticity of unknown form and are clustered at the establishment level. The interaction for March 2021 is excluded from each regression, so the effects can be interpreted as deviations from the outcome mean of the comparison group in the month prior to the 2021 reform.
Source: Authors' elaboration using data from the Mexican monthly manufacturing survey from 2018 to 2023.

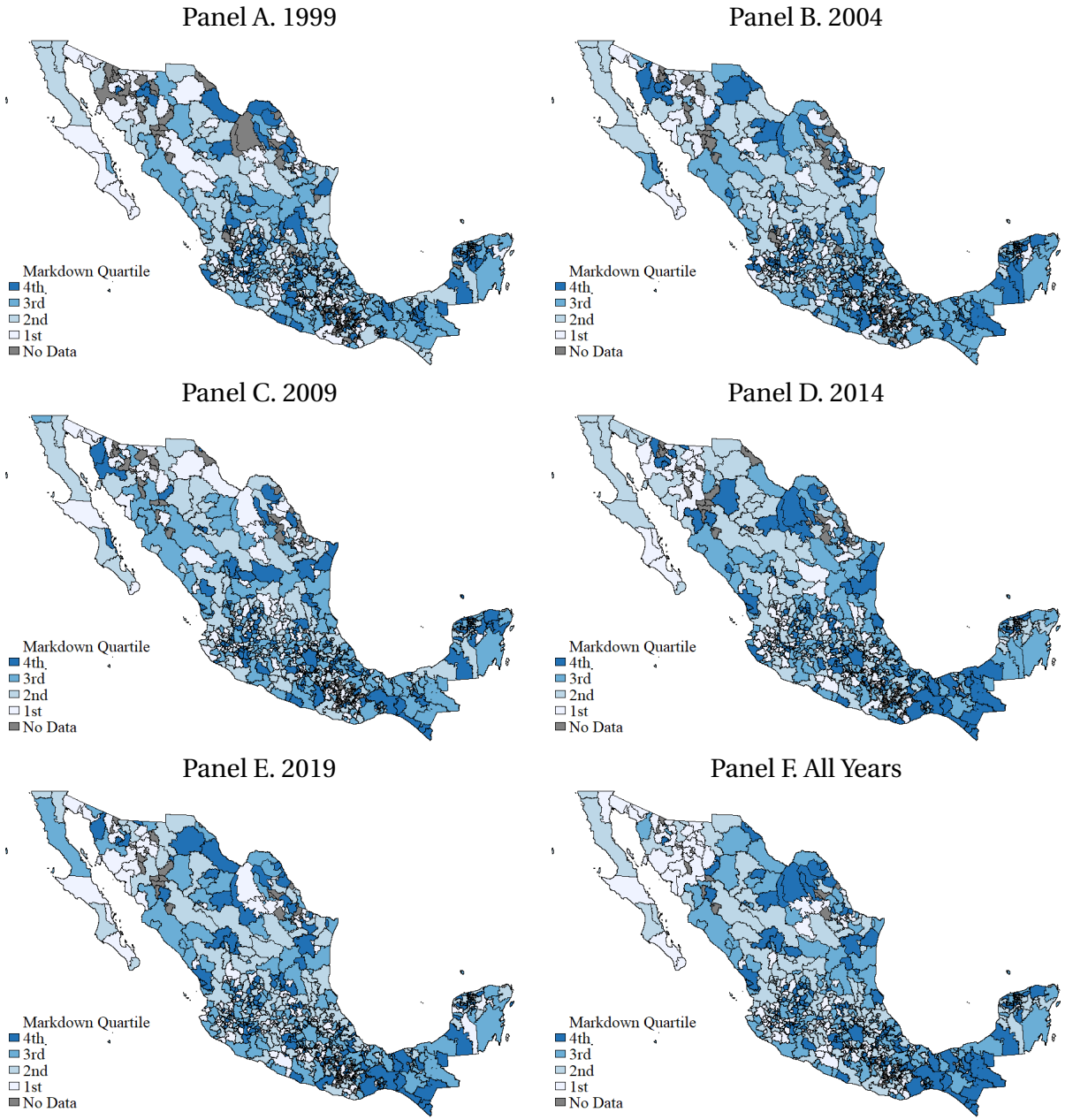
Table D.4: Dichotomous Treatment – Causal Impacts of the Reform on Monthly Outcomes

		Panel A. Outsourcing	
Regressor	All Workers	Some Workers	No Workers
	(1)	(2)	(3)
$\text{Outsourcing}_{i,\text{June 2020}} \times \text{Post}_t$	-0.54***	-0.22***	0.76***
	(0.01)	(0.01)	(0.01)
N	577,501	577,501	577,501
R^2	0.238	0.049	0.457
		Panel B. Employment	
Regressor	Insourced	Outsourced	Total
	(4)	(5)	(6)
$\text{Outsourcing}_{i,\text{June 2020}} \times \text{Post}_t$	0.62***	-0.59***	0.04
	(0.05)	(0.01)	(0.05)
N	577,501	577,501	577,501
R^2	0.0054	0.056	0.00003
		Panel C. Wages	
Regressor	Insourced Pay/Total Workers	Outsourced Pay/Total Workers	Total Pay/Total Workers
	(7)	(8)	(9)
$\text{Outsourcing}_{i,\text{June 2020}} \times \text{Post}_t$	0.87***	-0.62***	0.25***
	(0.02)	(0.01)	(0.02)
N	577,501	577,501	577,501
R^2	0.077	0.184	0.011
		Panel D. Insourced Wage Components	
	Salaries	Social Security and Benefits	Profit Sharing
	(10)	(11)	(12)
$\text{Outsourcing}_{i,\text{June 2020}} \times \text{Post}_t$	0.61***	0.21***	0.48***
	(0.01)	(0.01)	(0.01)
N	577,501	577,501	577,501
R^2	0.093	0.066	0.009

Notes: All regressions include all observations in the monthly manufacturing panel. The effects shown correspond to impacts 12 months after the reform. The measure of cross-sectional exposure to the reform is an indicator for the event of the establishment's outsourced employment share in June 2020 being above the cross-sectional median of that month. The effects in Panel B are expressed relative to the mean employment level across all establishments in the year prior to the reform (i.e., March 2020–March 2021). The effects in Panels C and D are expressed relative to the mean total wage compensation across all establishments in the year prior to the reform. All monetary amounts are deflated with the intermediate inputs subindex of Mexico's GDP deflator, the *índice nacional de precios al productor* (INPP). Standard errors are robust to heteroskedasticity of unknown form and are clustered at the establishment level. ***p<0.01.
Source: Authors' elaboration using data from the Mexican monthly manufacturing survey from 2018 to 2023.

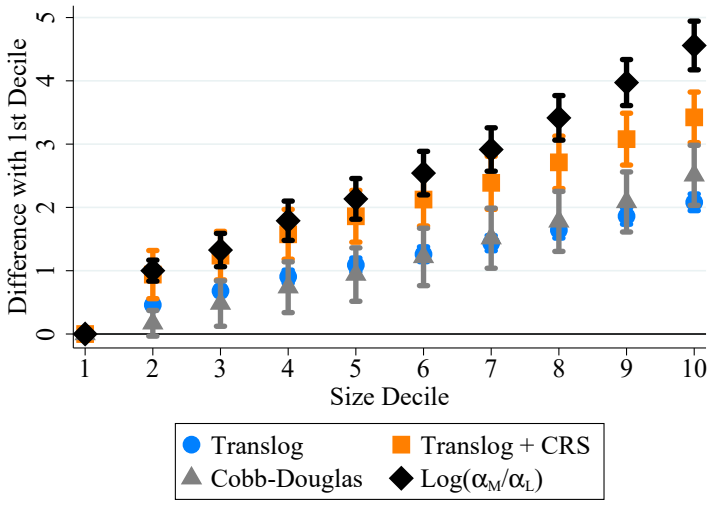
D.3 Commuting Zones as Local Labor Market Definition

Figure D.5: Average Markdown in Manufacturing by Commuting Zone and Census Wave



Notes: Each shade in the figure denotes a different quartile of the average markdown distribution, with lighter shades representing lower quartiles and darker shades representing higher quartiles. Quartiles in Panels A through E are taken with respect to the cross-sectional distribution of average markdowns at the commuting zone level by year, whereas Panel F depicts quartiles with respect to the distribution of average markdowns taken over all establishments and years at the commuting zone level. We estimate markdowns assuming that the production function is translog with parameters that vary at the 3-digit 1997 NAICS industry code level.
Source: Authors' elaboration using data from the Mexican economic census.

Figure D.6: Commuting Zones as Markets – Markdown Gradient with Establishment Size



Notes: This figure reports the coefficients and 95 percent confidence intervals of establishment size decile dummies, where the deciles are taken with respect to the national distribution of establishment shares of total revenue in their respective local labor markets, in a regression of wage markdowns on these dummies, local labor market fixed effects, and year indicators. Each marker type represents a different markdown measure. Standard errors are robust to heteroskedasticity of unknown form and are clustered at the market level. Markets are 3-digit NAICS industry code × commuting zone pairs. The reference group for the coefficient estimates are the establishments in the first size bin. Regressions pool data from the economic census waves from 1999 to 2019. N=230,185.
Source: Authors' elaboration using data from the Mexican economic census.

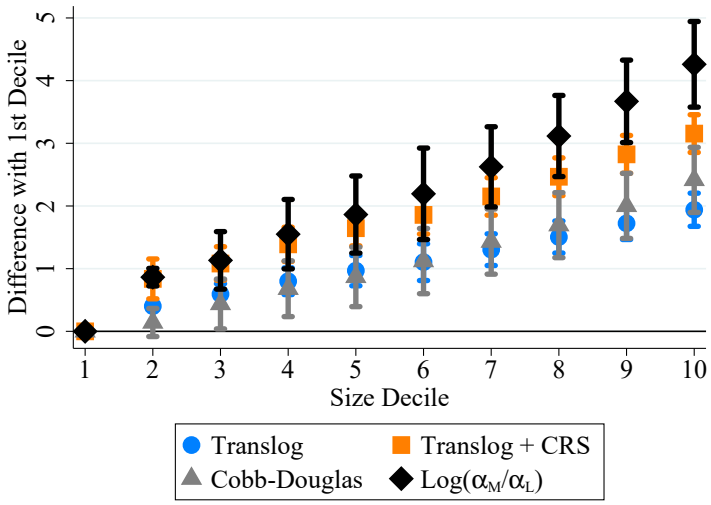
Table D.5: Commuting Zones as Local Markets – Outsourcing and Establishment Size
Outcome Variable: Share of Outsourced Employees

Regressor	(1)	(2)
Employment Share of Local Labor Market	0.08***	
	(0.006)	
Revenue Share of Local Labor Market		0.08***
		(0.005)
N	230,132	230,132
R^2	0.084	0.0856

Notes: All regressions include market fixed effects and time dummies. Standard errors are robust to heteroskedasticity of unknown form and are clustered at the establishment level. Markets are 3-digit NAICS industry code × commuting zone pairs. ***p<0.01.
Source: Authors' elaboration using data from the Mexican economic census waves from 1994 to 2019.

D.4 Markdowns and Outsourcing Gradients with Firm-Level Revenue

Figure D.7: Markdown Gradient with Firm Size



Notes: This figure reports the coefficients and 95 percent confidence intervals of firm size decile dummies, where the deciles are taken with respect to the national distribution of firm shares of total revenue in their respective local labor markets, in a regression of establishment-level wage markdowns on these dummies, local labor market fixed effects, and year indicators. Each marker type represents a different markdown measure. Standard errors are robust to heteroskedasticity of unknown form and are clustered at the market level. Markets are 3-digit NAICS industry code × metropolitan area/municipality pairs. The reference group for the coefficient estimates are the firms in the first firm size bin. The regression pools data from the economic census waves from 1999 to 2019. N=229,717.
Source: Authors' elaboration using data from the Mexican economic census.

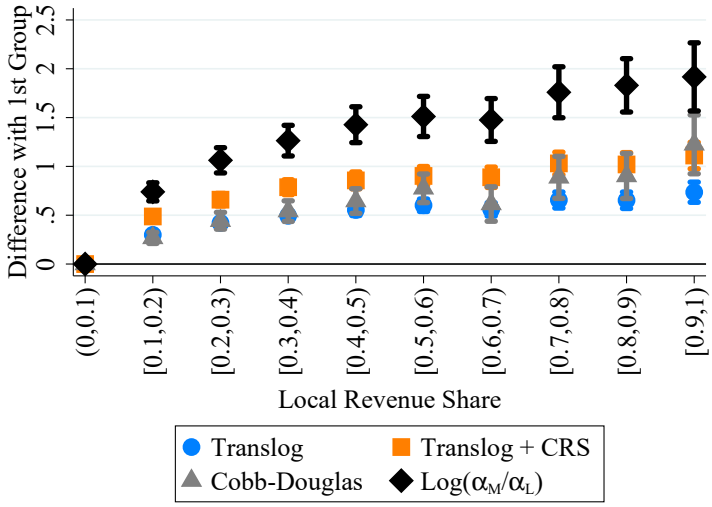
Table D.6: Outsourcing and Firm Size
Outcome Variable: Firm Share of Outsourced Employees

Regressor	(1)	(2)
Firm Employment Share of Local Labor Market	0.07***	
	(0.005)	
Firm Revenue Share of Local Labor Market		0.06***
		(0.004)
N	228,717	228,717
R^2	0.089	0.09

Notes: Firms are the unit of observation. All regressions include firm fixed effects and time dummies. Standard errors are robust to heteroskedasticity of unknown form and are clustered at the firm level. Markets are 3-digit NAICS industry code × metropolitan area/municipality pairs. ***p<0.01.
Source: Authors' elaboration using data from the Mexican economic census waves from 1994 to 2019.

D.5 Markdown Gradient under an Alternative Partition of the Size Range

Figure D.8: Markdown Gradient under an Alternative Partition of the Size Range



Notes: This figure reports the coefficients and 95 percent confidence intervals of establishment size category dummies in a regression of wage markdowns on these dummies, establishment fixed effects, and year indicators. Each marker type represents a different markdown measure. Establishment size is defined as the establishment share of total revenue in its local labor market. Standard errors are robust to heteroskedasticity of unknown form and are clustered at the establishment level. Markets are 3-digit NAICS industry codes × metropolitan area/municipality pairs. The reference group for the coefficient estimates are the establishments in the first size category. The regression pools data from the economic census waves from 1999 to 2019. N=226,784.
Source: Authors' elaboration using data from the Mexican economic census.