The Decline of Labor Market Power in Spain

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BdE-CEMFI-UIMP Conference on the Spanish Economy
Santander, July 4, 2024

WORK IN PROGRESS

Introduction

- Firms have a substantial degree of market power relative to their workers in the United States (Yeh, et al., 2022, Kirov and Traina, 2022).
- Firms' labor market power has increased in the United States in recent decades (Kirov and Traina, 2022) or remained stable (Yeh et al., 2022).
- In Europe, markdowns have generally also increased (Mertens, 2022; Diez et al, 2023).
- The Spanish labor market has unique characteristics that could imply different labor market dynamics relative to other countries, even European ones:
  - High degree of labor market duality and rigidity.
  - High unemployment.
- For example, looking at product markets, García-Perea, Lacuesta, and Roldan-Blanco (2021) study the evolution of markups in Spain:
  - They find an increase in markups, as in other countries.
  - However, unlike in other countries, the covariance between firm size and markups is negative among Spanish firms.
  - The increase in markups was driven by a reallocation from large firms to small firms.

What This Paper Does

- Measure markdowns for Spanish firms using BdE balance sheet data over the period 1997-2021, using a **revenue-production function approach**.
- Characterize the distribution and evolution of markdowns over this period.
- Examine the relation of markdowns with firm size, labor market concentration, temporary employment share, and female employment share.
- Event study examining the effect of the labor market liberalization reforms of 2012.
- The liberalization allowed firms to negotiate with their workers without being bound by sector-level agreements (Izquierdo, Lacuesta, and Puente, 2013; Malo, 2015).
    - We look at the effect on firm-level employment, wages, labor market power, productivity, and temporary employment.
    - We study heterogeneity by:
        1. The initial level of labor market power.
        2. Firm size categories (large, medium, small, and micro).

Preview of Results: Markdowns

- Labor market power *declined* for Spanish firms over this period.
- Largest decline was around the Great Financial Crisis of 2008.
- The weighted-average markdown went from around 30% before the crisis to around 10% after the crisis, increasing again to around 15% in 2021.
  - This drop in markdowns was driven primarily by a decline in the marginal revenue product of labor (MRPL), rather than an increase in wages.
  - Markdowns remained positive for large and medium-sized firms, while becoming close to zero for small firms, and turning negative for micro firms.
  - Labor market concentration also declined over this period.
- Markdowns are positively associated with female employment, and with temporary employment.
- There is a positive relationship between markdowns and concentration.

Preview of Results: Event Study

- On average the labor market liberalization had no significant effect on employment or wages, but it had a positive effect on the markdown.
- Substantial heterogeneity by pre-period markdowns and firm size:
  1. Employment:
     - ⋆ No effect for large. Expanded for medium, small, and micro.
     - ⋆ Contracted for low-markdown, expanded for high-markdown.
  2. Wages:
     - ⋆ No effect for large. Small decline for medium. Temporary increase for small. Temporary decrease for micro.
     - ⋆ No effect on low-markdown. Declined for high-markdown.
  3. Markdown:
     - ⋆ Increase for large. No effect for medium or small. Decrease for micro.
     - ⋆ No effect for low-markdown. Increase for high-markdown.
  4. Productivity:
     - ⋆ Small decline for large firms, no effect on medium. Large increase for small and micro.
     - ⋆ No clear heterogeneity by markdowns.
  5. Temporary employment:
     - ⋆ No clear effect for any firm size.
     - ⋆ Small decrease for low markdown. Increase for high markdown.

Data

- We use data from the Bank of Spain's *Central de Balances Integrada* (CBI), covering more than 2 million Spanish firms over the period 1995 to 2022.
- This covers about 80% of employment in the Spanish economy since 2002 or so (Almunia, Lopez-Rodrigues, and Morales-Benito, 2018).
- It includes data on the firms' balance sheets and income statements, geographic and sector infromation, as well as information on wages, female employment and employment of temporary workers.
- We merge these with data on union coverage by 2-digit NACE sector times autonomous community from the Ministry of Labor.
- We trim observations with wages in the bottom and top percentiles, and with employment above the 99.99th percentile (due to very high values that are apparent errors).

Markdown Estimation: Methodology

- A monopsonistic firm's profit maximization problem is:

$$\max_{L} R(L) - w(L)L. \tag{1}$$

- The first-order condition with respect to employment is:

$$R'(L) = w(L) + w'(L)L. \tag{2}$$

  Dividing by $w(L)$, we obtain an inverse-elasticity rule for the markdown ν:

$$\nu \equiv \frac{R'(L)}{w(L)} = 1 + \frac{w'(L)L}{w(L)}. \tag{3}$$

- One approach to estimating the markdown is based on the right-hand side: estimating the elasticity of labor supply to the firm.
- Alternatively, we can estimate the markdown "directly" from the left-hand side, by estimating the marginal revenue product of labor (MRPL) $R'(L)$.

Markdown Estimation: Methodology (cont.)

- Given the elasticity of revenue with respect to employment $\theta^{R,L}$ and the labor share of revenue α^L, we can rewrite the left-hand-side expression for the markdown ν as

$$\nu = \frac{R'(L)\frac{L}{R(L)}}{w(L)\frac{L}{R(L)}} = \frac{\theta^{R,L}}{\alpha^L}. \tag{4}$$

- Most of the production function estimation literature (including the markup estimation literature) are interested in the elasticity of *output* with respect to employment $\theta^{Q,L}$.
- The fact that most datasets contain revenues but not output is a significant issue in this literature (Klette and Griliches, 1996; Bond et al., 2021).
- A substantial body of literature has emerged on estimation of output elasticities from revenue data (Flynn, et al, 2019; Gandhi, et al., 2020; Kirov and Traina, 2021, 2023).
- However, to estimate markdowns, the revenue elasticity is *exactly* what we need (Hashemi, et al., 2022).

Bond et al. (2021) Critique

- Bond et al. (2021) critique the markup estimation literature by noting that applying the markup formula with a revenue instead of an output elasticity yields no information on the markup:

$$
\begin{aligned}
\frac{\theta^{R,M}}{\alpha^M} &= \frac{\theta^{Q,M}}{\alpha^M}\left(1 + \frac{dP(Q)}{dQ}\frac{Q}{P}\right) && (5)\\
&\equiv \frac{\theta^{Q,M}}{\alpha^M}\left(1 + \varepsilon_{P,Q}\right) && (6)\\
&= \mu \times \left(1 + \varepsilon_{P,Q}\right) && (7)\\
&= 1. \text{ (Product market inverse-elasticity rule)} && (8)
\end{aligned}
$$

- This critique does not apply to our estimator of the markdown, because it actually requires the *revenue* elasticity, not the *output* elasticity.
- This is a consequence of the markdown definition naturally being based on the marginal *revenue* product of labor.

Comparison to Yeh et al. (2022)

- Yeh et al. (2022) derive a similar formula for the markdown, based on the elasticity of *output* with respect to labor. Because they use the output elasticity, the formula requires dividing by the markup μ:

$$\nu^{YHM} = \frac{1}{\mu} \frac{\theta^{Q,L}}{\alpha_L}. \tag{9}$$

- The two formulas, (9) and (4), are equivalent because the revenue elasticity is equal to the output elasticity divided by the markup: $\theta^{R,L} = \theta^{Q,L} / \mu$.
- The key assumption they use to estimate the markup is the existence of a frictionless input M (materials): $\mu = \theta^{Q,L} / \alpha^L$.
- To respond to the Bond et al. (2021) critique, they show that, when using revenue elasticities instead of output elasticities, the $(1 + \varepsilon_{P,Q})$ terms in $\theta^{R,L}$ and $\theta^{R,M}$ cancel out.
- However, this is true only because, theoretically, under the frictionless input assumption, the markup estimator $\theta^{R,M} / \alpha^M$ **equals one**, and the numerator $\theta^{R,L} / \alpha^L$ **is the markdown**.

Comparison with Yeh et al. (cont.)

- We follow instead, Hashemi et al. (2022)'s suggestion of using directly the formula based on the revenue elasticity derived above:

$$\nu = \frac{R'(L)\frac{L}{R(L)}}{w(L)\frac{L}{R(L)}} = \frac{\theta^{R,L}}{\alpha^{L}}. \tag{10}$$

- This means that we do not need to divide by the markup estimated using a flexible input (materials).
- With the methodology we use (suggested by Hashemi, et al., 2022, but not yet implemented empirically), we can lift the frictionless input assumption, and do not require additional data on input prices (other than wages for labor).

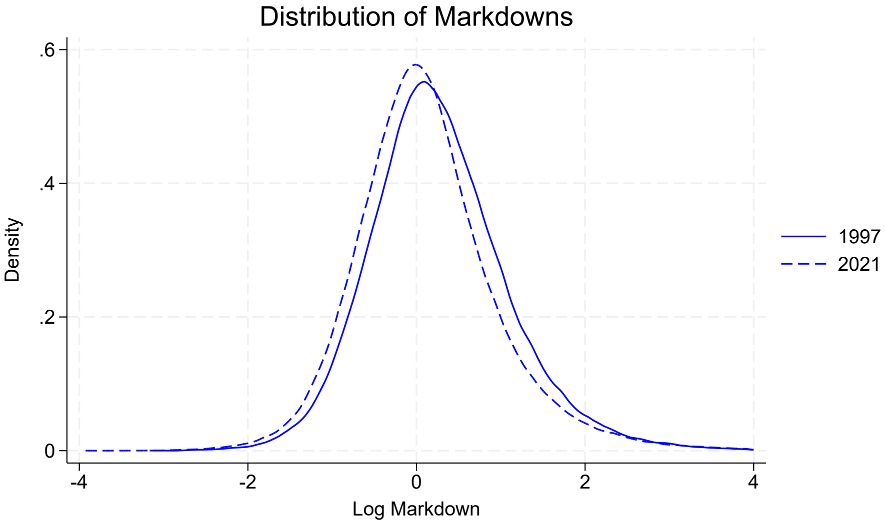
Revenue Production Function Estimation

- The firm's production function is

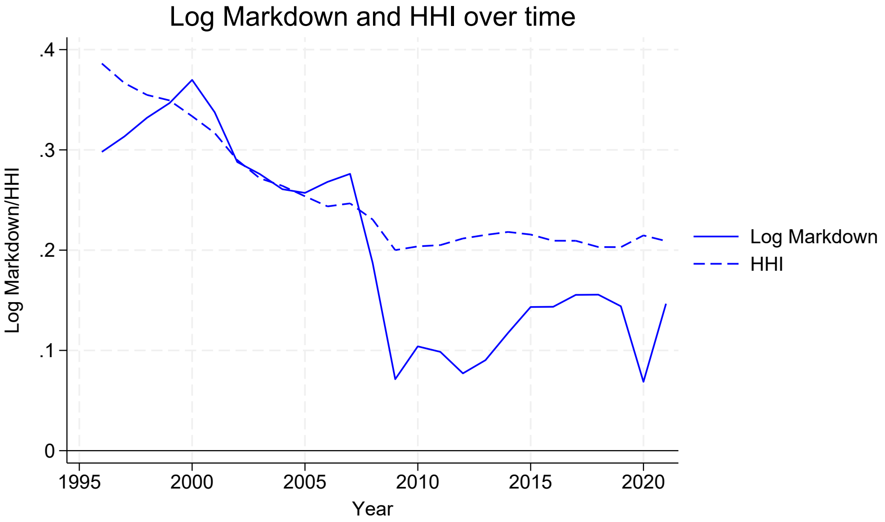
$$y_{it} = f(l_{it}, k_{it}, m_{it}; \beta) + \omega_{it} + \varepsilon_{it}. \qquad (11)$$

- The error ω_{it} is observed by the firm when deciding over the flexible inputs l and m, and is serially correlated. The error ε_{it} is uncorrelated and not observed by the firm until it has made its decisions. Estimation proceeds in three steps:
    1. Obtain φ_{it} by running y_{it} on a third-order polynomial in the inputs and calculating the predicted values.
    2. Given a candidate β, calculate ω_{it} and $\omega_{i,t-1}$ and project ω_{it} on a 5-th order polynomial in $\omega_{i,t-1}$, and obtain the residual ξ_{it}.
    3. Find the β that minimizes the GMM objective function summing the squared products of the residuals ξ_{it} and the instruments ($l_{i,t-1}$ and $m_{i,t-1}$).
- We estimate a Cobb-Douglas specification by 2-digit NACE sector.
- We use OLS to obtain initial values for the nonlinear GMM optimization.

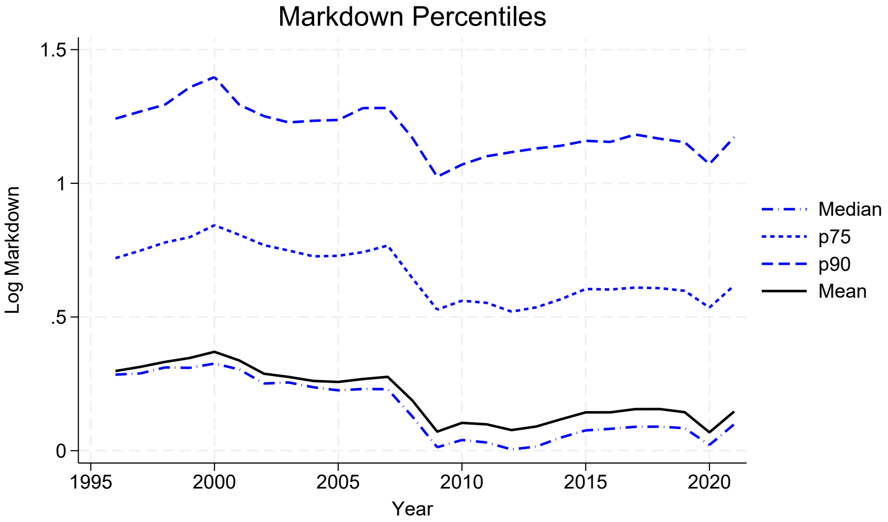
Density of Markdowns



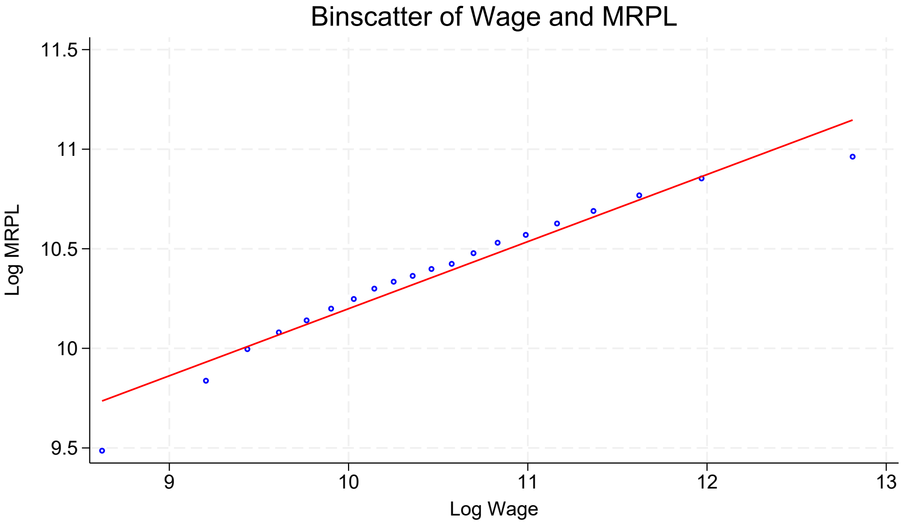
Markdowns and Labor Market Concentration over Time



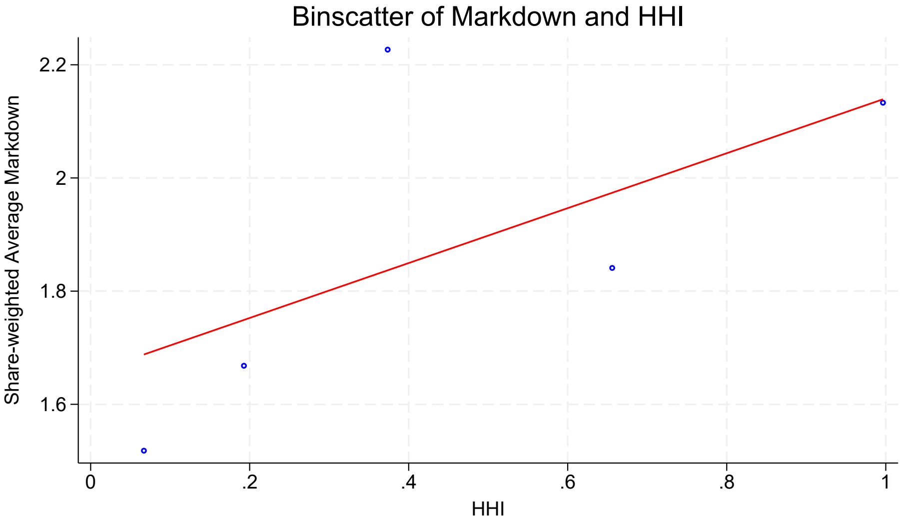
Distribution of Markdowns over Time



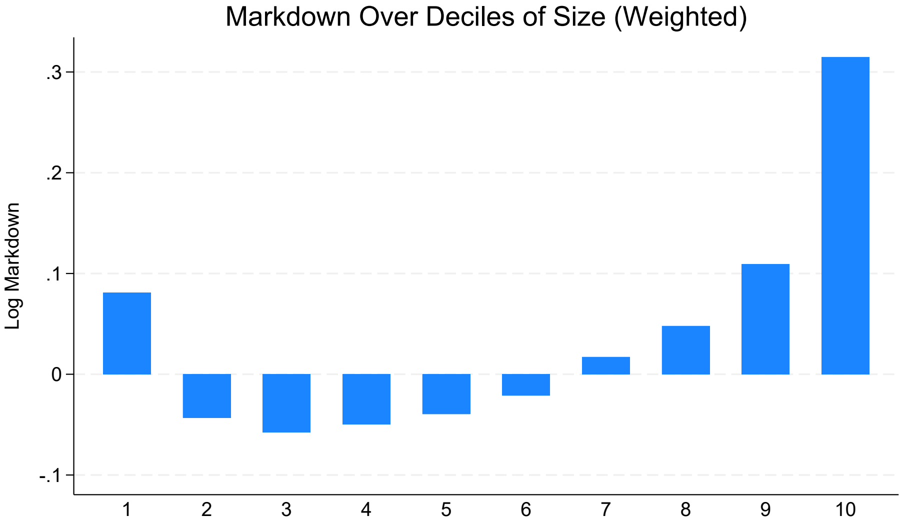
MRPL and Wages Binscatter



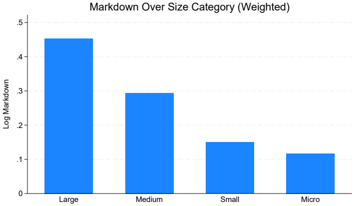
Markdowns and HHI Binscatter



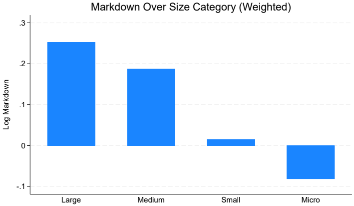
Markdowns by Decile of Labor Market Share



Markdowns by Firm Size, Before and After the Crisis of 2008

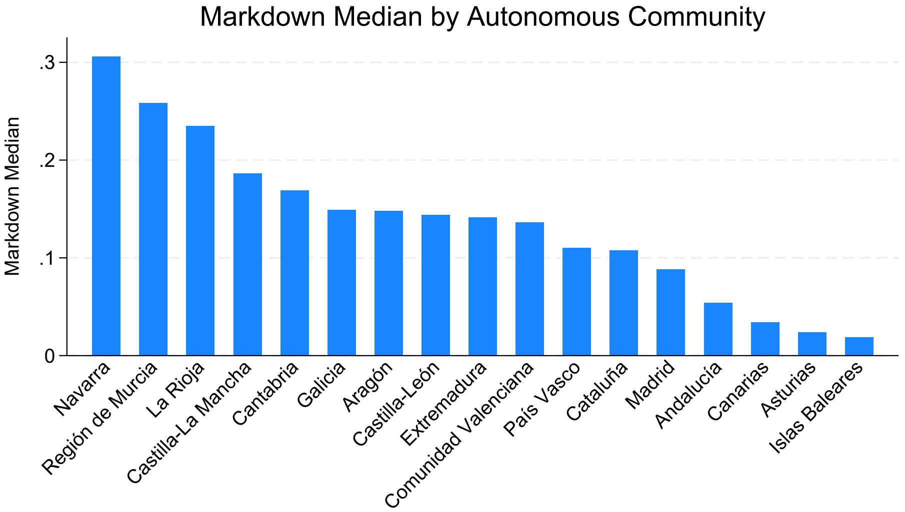


(a) Pre-2008

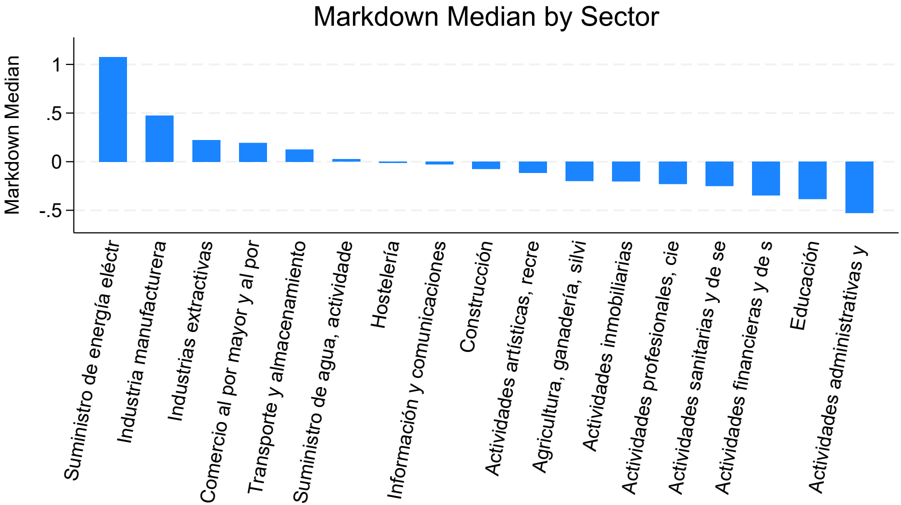


(b) Post-2008

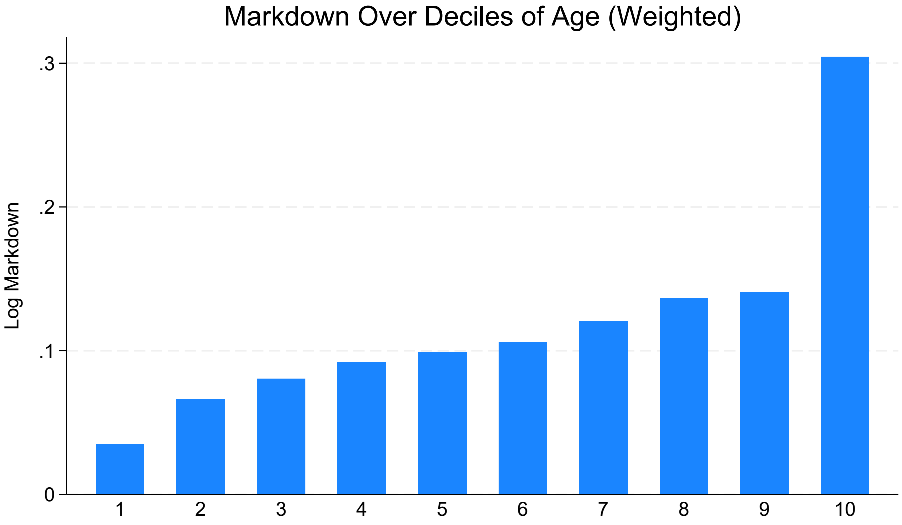
Markdowns by Autonomous Community



Markdowns by Autonomous Community



Markdowns and Firm Age



Markdowns and Temporary Employment

	Log wage		Log MRPL		Log Markdown	
	(1)	(2)	(3)	(4)	(5)	(6)
Log Temporary Employment	-0.0712***	-0.0154***	-0.0908***	0.0170***	-0.00610	0.0335***
	(0.00273)	(0.00138)	(0.00659)	(0.00369)	(0.00472)	(0.00382)
Log Employment	0.132***	-0.229***	0.186***	-0.354***	0.0385***	-0.0624***
	(0.00643)	(0.00835)	(0.0134)	(0.0157)	(0.00947)	(0.0142)
Log Employment^2	-0.00369***	0.0101***	-0.00555***	0.0134***	-0.000650	0.000675
	(0.000659)	(0.000890)	(0.00154)	(0.00232)	(0.00102)	(0.00192)
Publicly Traded	0.0506***	0.000414	0.135***	-0.0144	0.0666**	-0.0242
	(0.0148)	(0.00886)	(0.0450)	(0.0301)	(0.0267)	(0.0229)
Foreign Ownership	0.0668***	-0.00984	0.152***	0.0328**	0.0727***	0.0449***
	(0.00932)	(0.00609)	(0.0179)	(0.0140)	(0.0145)	(0.0138)
Province FE	✓		✓		✓	
Industry FE	✓		✓		✓	
Firm FE		✓		✓		✓
Age FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Observations	4,726,110	4,527,600	4,726,110	4,527,600	4,726,110	4,527,600
R-squared	0.576	0.903	0.554	0.920	0.475	0.899

Two-way clustered standard errors by firm and year in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Markdowns and Female Employment

	Log wage		Log MRPL		Log Markdown	
	(1)	(2)	(3)	(4)	(5)	(6)
Log Female Employment	-0.0225***	0.0226***	0.0661***	0.0499***	0.0946***	0.0159***
	(0.00463)	(0.00201)	(0.0122)	(0.00617)	(0.00693)	(0.00429)
Log Employment	0.118***	-0.247***	0.126***	-0.377***	-0.0158	-0.0584***
	(0.00676)	(0.0136)	(0.0186)	(0.0266)	(0.0139)	(0.0167)
Log Employment^2	-0.00826***	0.00712***	-0.0166***	0.0104***	-0.00511***	0.000484
	(0.000759)	(0.00117)	(0.00187)	(0.00269)	(0.00134)	(0.00257)
Publicly Traded	0.0722***	-0.00368	0.174**	-0.000372	0.0862**	-0.0117
	(0.0197)	(0.0102)	(0.0610)	(0.0193)	(0.0307)	(0.0149)
Foreign Ownership	0.113***	0.00475	0.182***	0.00541	0.0429**	0.00409
	(0.00893)	(0.00410)	(0.0218)	(0.0122)	(0.0167)	(0.0106)
Province FE	✓		✓		✓	
Industry FE	✓		✓		✓	
Firm FE		✓		✓		✓
Age FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Observations						
Observations	2,539,390	2,403,577	2,539,390	2,403,577	2,539,390	2,403,577
R-squared	0.555	0.933	0.530	0.942	0.480	0.933

Two-way clustered standard errors by firm and year in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Event Study: Labor Market Liberalization of 2012

- In 2012, Spain passed a major labor market liberalization reform.
- The liberalization allowed firms to negotiate their own agreements instead of being bound by the sectoral agreements (Izquierdo, Lacuesta, and Puente, 2013; Malo, 2015).
- We use data on union coverage by sector$\times$CCAA to identify treatments and controls. In particular, we use sector$\times$CCAA's with zero union coverage in 2011 as controls, and the rest as treatments.
- We conduct an event-study using a balanced panel of firms over the period 2005-2019.
- We estimate the Average Treatment Effect on the Treated (ATET) using the Difference-in-Differences methodology with multiple time periods of Calloway and Sant'Anna (2021) (`xthdidregress` command in Stata).
- We match treatment and control firm sizes by using an inverse-probability weights (IPW) methodology, with the propensity scores estimated using pre-period levels of employment, capital, and wages.
- We weigh firms by their pre-period employment level.

Outcome Variables

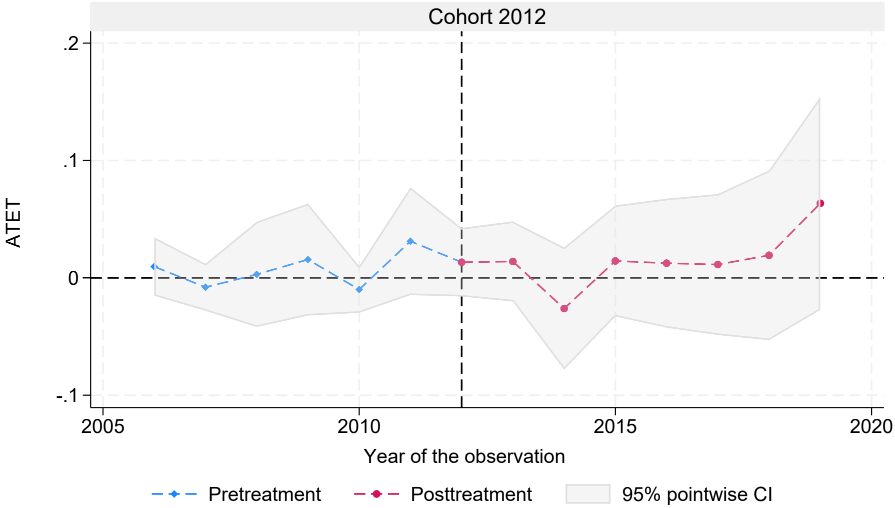
- We study the effect of the treatment on the following outcome variables:
  1. Log Employment
  2. Log Wage
  3. Log Markdown / Log Labor Share*
  4. Log Total Factor Revenue Productivity (TFRP)
  5. Log Marginal Revenue Product of Labor (MRPL)
  6. Share of Temporary Employment
- Data on female employment starts in 2010, so it doesn't fit our balanced panel's period. However, we could run this for the period 2010-2019 (soon).

*The effect on the labor share and the markdown are the negative of each other, since the log markdown is the log elasticity minus the log labor share, and the elasticity is constant over time within-firm.

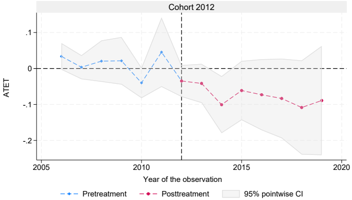
Heterogeneity by Markdown and Size Category

- We study the heterogeneity in the ATT by pre-period markdown, and by pre-period firm-size category (large, medium, small, micro).
- We categorize firms into high-markdown and low-markdown based on their average estimated markdowns in the pre-period.
- In particular, if a firm's pre-period markdown is below the median pre-period markdown, we classify the firm as low-markdown, and if it is above, we classify it as high-markdown.
- We also construct our own size categories based on employment in 2011:
    1. Large: > 250.
    2. Medium: $\in (50, 250]$.
    3. Small: $\in (10, 50]$.
    4. Micro: ≤ 10.
- We run separate DiD regressions by size category and markdown.

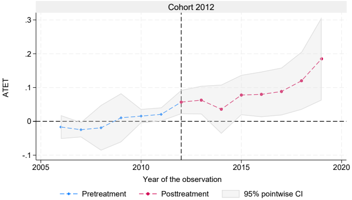
Effect on Employment



Effect on Employment: Heterogeneity by Pre-Period Markdown

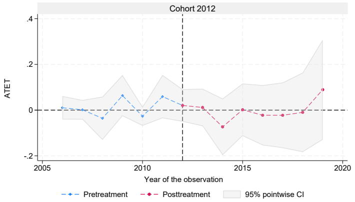


(a) Low Markdown

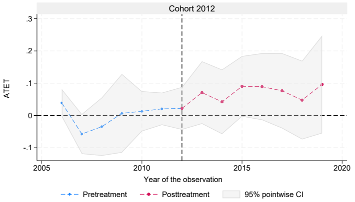


(b) High Markdown

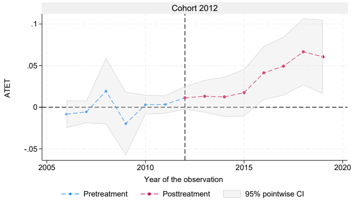
Effect on Employment: Heterogeneity by Size Category



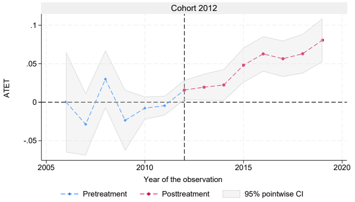
(a) Large



(b) Medium



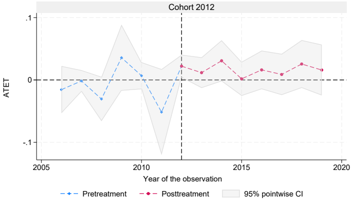
(c) Small



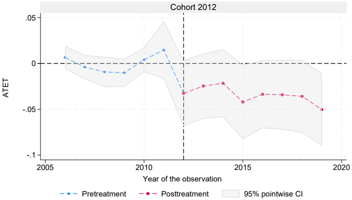
(d) Micro

Effect on Wages

Effect on Wages: Heterogeneity by Pre-Period Markdown

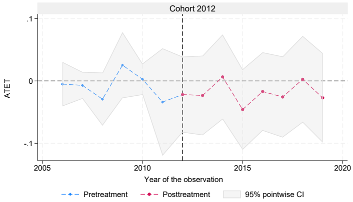


(a) Low Markdown

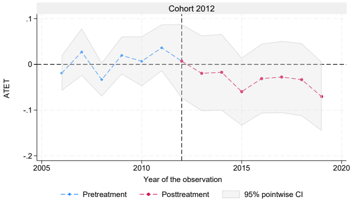


(b) High Markdown

Effect on Wages: Heterogeneity by Size Category

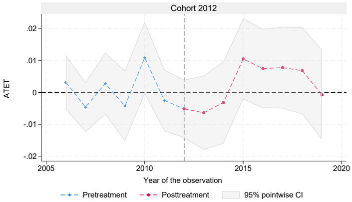


(a) Large



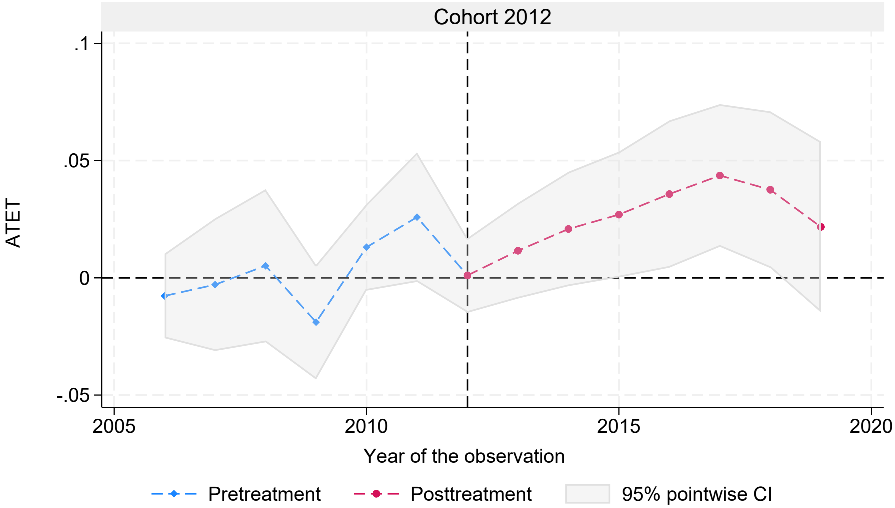
(b) Medium

(c) Small

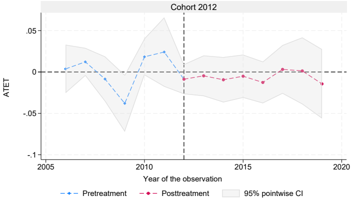


(d) Micro

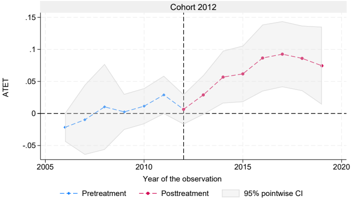
Effect on Markdowns



Effect on Markdowns: Heterogeneity by Pre-Period Markdown

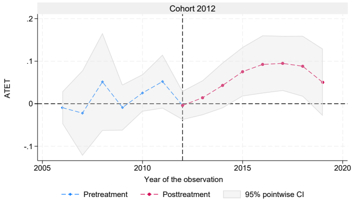


(a) Low Markdown

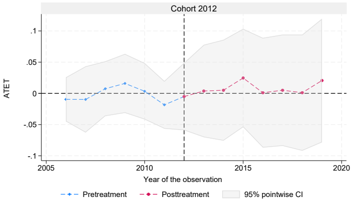


(b) High Markdown

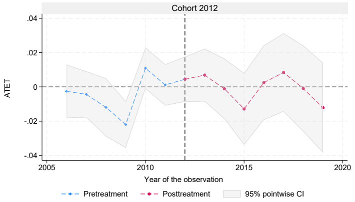
Effect on Markdowns: Heterogeneity by Size Category



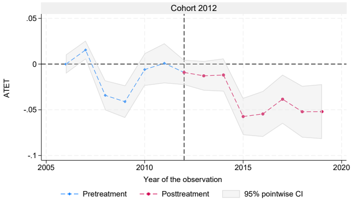
(a) Large



(b) Medium

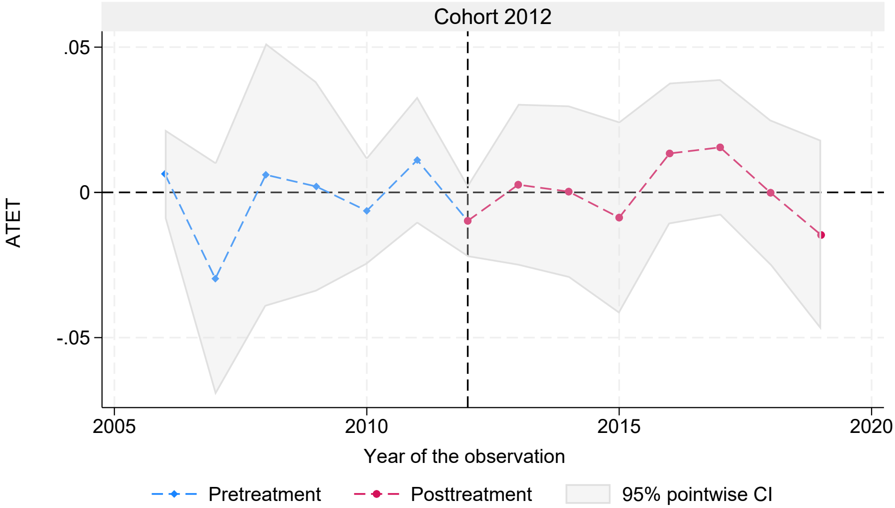


(c) Small

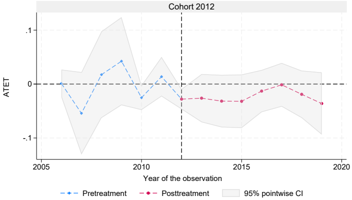


(d) Micro

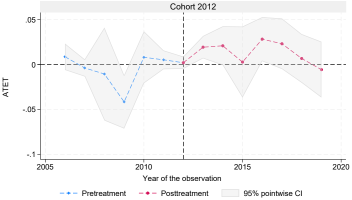
Effect on Total Factor Productivity of Revenue



Effect on TFPR: Heterogeneity by Pre-Period Markdown

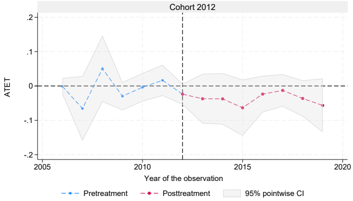


(a) Low Markdown

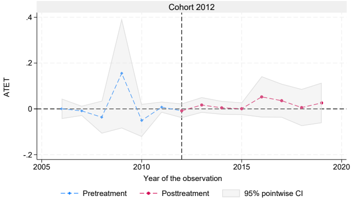


(b) High Markdown

Effect on TFPR: Heterogeneity by Size Category

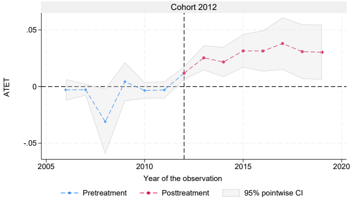


(a) Large



(b) Medium

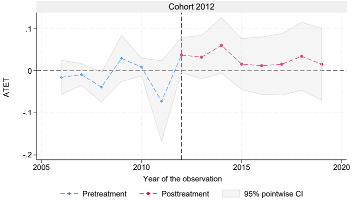
(c) Small



(d) Micro

Effect on Marginal Revenue Product of Labor

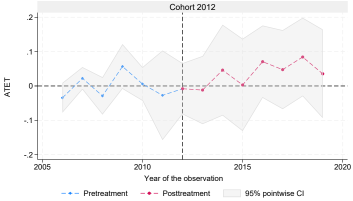
Effect on MRPL: Heterogeneity by Pre-Period Markdown



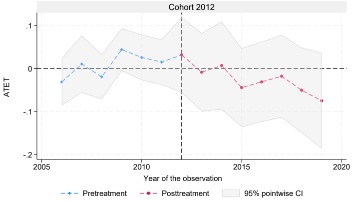
(a) Low Markdown

(b) High Markdown

Effect on MRPL: Heterogeneity by Size Category

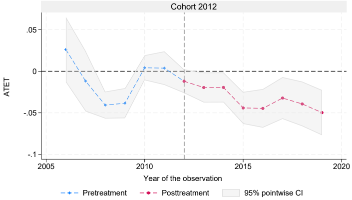


(a) Large



(b) Medium

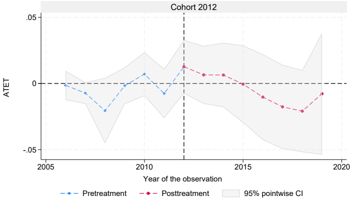
(c) Small



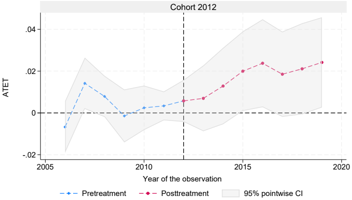
(d) Micro

Effect on Share of Temporary Employment

Effect on Temp Share: Heterogeneity by Pre-Period Markdown

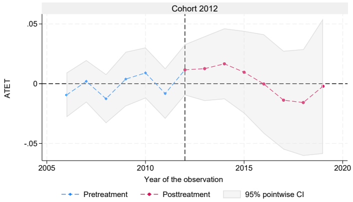


(a) Low Markdown

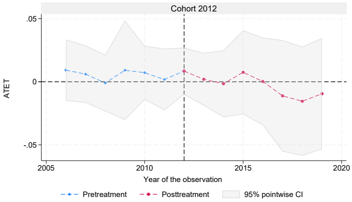


(b) High Markdown

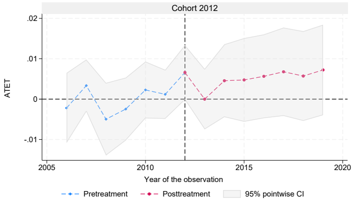
Effect on Temp Share: Heterogeneity by Size Category



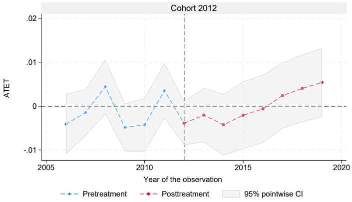
(a) Large



(b) Medium



(c) Small



(d) Micro

Concluding Remarks

- Weighted-average markdowns in Spain have declined since the 1990s.
- This decline was especially pronouced around the crisis of 2008, and driven by MRPL declining faster than wages.
- Markdowns remain positive for large and medium-size firms, but are now near-zero for small firms, and negative for micro firms.
- Markdowns are positively associated with female and temporary employment.
- There is a U-shaped relationship between markdowns and labor market share.
- There is a positive relationship between markdowns and labor market concentration.
- The reforms of 2012:
  - Had no effect on employment or wages on average, but increased markdowns.
  - Increased employment for high-markdown firms. Reduced it for low markdown.
  - Increased employment for medium, small, and micro firms. No effect on large.
  - Increased productivity for small and micro firms.
  - Reduced wages and increased markdown for firms with high-markdowns in the pre-period.

Concluding Remarks (cont.)

- These results suggest that labor market liberalization reduced employees' bargaining power, while having a positive effect on the productivity and employment of small firms.
- The largest effects are in general observed in high-markdown firms:
  1. Increase in employment.
  2. Decrease in wages.
  3. Increase in the markdown.
  4. Increase in temporary employment.
- An interesting question now is whether existing models of labor market power (classical oligopsony, search, etc.) are consistent with our findings.