1 Introduction

There has been a recent surge in the literature that studies firms' market power in the labor market. While one strand of literature has focused on measuring firms' monopsony power calculating the Herfindahl-Hirschman Index in vacancies (Jarosch et al., 2019; Azar et al., 2020) or wage bills (Lamadon et al., 2022; Berger et al., 2022), others estimate markdowns recovering elasticities from balance sheets (Yeh et al., 2022; Deb et al., 2022a,b).[1] An accurate assessment of the degree and dynamics of market power in labor markets is critical for the design of policy responses aimed at mitigating the (mis)allocation costs of market power and achieving efficient outcomes. However, most of these studies focus on the US and the manufacturing sector, while evidence on a broader set of countries and industries is scant with a few exceptions (e.g. Mertens (2022)). This paper aims at filling this gap—namely, we explore whether similar trends in corporate market power in labor markets is found in other advanced economies other than the United States and, moreover, whether there are sizable differences across sectors.[2]

Similarly to Yeh et al. (2022), we use balance sheet data from 10 European countries to estimate firm-level markdowns. These markdowns, defined as the ratio of the marginal revenue of labor to wages is the main object to measure labor market power—a markdown above 1 suggests that the firm receives a marginal revenue higher than the wage paid (to the marginal) worker, an indication of the firm's market power. Our estimates allow us to establish the following stylized facts:

F1: *Most firms have markdowns above 1.*

F2: *The weighted-average markdown increased 1.3% between 2000 and 2017.*

F3: *The median markdown decreased almost 10% over the same period.*

F4: *High-markdown firms are large in product and input markets, and are likely to be listed and in service sectors.*

F5: *The reallocation of resources towards high-markdown firms offsets the decrease in within-firm markdowns.*

We begin by documenting that labor market power is pervasive in Europe. Indeed, the vast majority of firms, present markdown values above unity, suggesting some measure of

[1] Others (Manning, 2003, 2021) approach this issue using turnover based approach.

[2] This literature on labor market power is contemporaneous to the another strand focused on market power in product markets (De Loecker et al., 2020), that has found an overall increase in market power, but particularly large in the United States and in service sectors (Díez et al., 2021).

market power—this is widespread across countries and sectors. Focusing on the dynamics, we find that weighted average markdowns have increased (slightly) in recent years, which would suggest that labor market power is becoming increasingly concerning. However, the median and simple average markdown actually declined (and strongly) over the same period, indicating the existence of substantial heterogeneity across firms: markdowns declined for the entire distribution of firms except for the top 1% with the highest average markdowns. Next, we characterize these high-markdown firms. We find that high markdowns are associated with high shares in local goods and labor markets. In other words, these firms have a sizable footprint in both, product and input markets. Further, we find that these firms are significantly larger (unconditionally of the market in which they operate) and are more likely to be listed and in service sectors—we find a sizable increase in weighted average markdowns in services, in sharp contrast with the flat markdowns found for goods-producing sectors.

Finally, a Melitz-Polanec decomposition of the change in markdowns confirms these divergent paths. Indeed, we find that there is a clear decline in markdowns among incumbents (the *within-firm* component of the decomposition). However, this effect is offset by the reallocation of resources toward high-markdown firms among incumbent firms and (net) entrants, which drive the average increase in markdowns.

Our paper makes contributions to (at least) three different strands of the literature. First, we contribute to the aforementioned recent literature on labor market power (that has found an increase in corporate labor market power, mostly in the United States) by highlighting the different dynamics observed across European countries and across economic sectors. Second, we also contribute to the overall literature on market power (De Loecker et al., 2020; **?**; Díez et al., 2021), that has focused mostly on market power in product markets, by showing how firms with labor market power also have a sizable footprint in product markets–suggesting the importance of taking a "holistic" approach to study all dimensions of corporate market power simultaneously. Finally, we contribute to the broad literature on firm dynamics and the divergent path of a small group of (sometimes labeled superstar) firms (Autor et al., 2020; Gutiérrez and Philippon, 2019; Andrews et al., 2016) by showing how high-markdown firms offer opposite dynamics to the rest of firms.

The rest of the paper is organized as follows. We first describe our methodology and data in sections 2 and 3. Section 4 presents our headline results, describing recent markdown dynamics in Europe and stressing the differences across countries and sectors. Section 5 focuses on firm-level differences for different segments of the markdown distribution and quantifies the roles of within-firm and reallocation effects in explaining aggregate markdown changes. Finally, Section 6 concludes.

2 Markdown Estimation

As already mentioned, markdowns are our measure of corporate market power in labor markets. Under competitive markets, the marginal revenue of labor must be equal to the marginal cost of labor (wage). However, market power creates a wedge in this equality condition—which is precisely the markdown. Traditionally, obtaining accurate measures of markdowns was difficult; however, the availability of firm-level data and advances in the literature, particularly the new literature on mark*ups*, have greatly eased markdown estimation. We follow the so-called production function approach put forward by the seminal paper on markup estimation by De Loecker and Warzynski (2012). The estimation requires some assumptions on the firm profit maximization problem. Most notably, it requires (i) the existence of an observable fully flexible input and (ii) that labor inputs can also be adjusted flexibly. The first assumption is standard when estimating markups. The second assumption is crucial in our baseline estimation, but can be relaxed. In this section, we show how to recover markdowns under both assumptions, but section A.3 in the appendix shows how to adjust the estimates if one allows for labor adjustment costs.

2.1 The firm problem under labor market power

To fix ideas on the role of markdowns, consider a simple static profit maximization problem, under the assumption that all inputs other than labor are at their optimal level:

$$\max_{l} R(l) - w(l)l$$

The optimality condition for the choice of the labor input reads

$$R'(l) - w'(l)l - w(l) = 0 \tag{1}$$

and after some rearranging, implies the following relationship between the (revenue) marginal product of labor $R'(l)$ and the inverse elasticity of residual labor supply facing the firm $\varepsilon_{L^S}^{-1}$:

$$R'(l) = (\varepsilon_{L^S}^{-1} + 1)w(l) \tag{2}$$

Dividing both sides of the previous equation by the wage $w(l)$, we obtain an expression that links markdown (ν) and inverse elasticity of (residual) labor supply ($\varepsilon_{L^S}^{-1}$):

$$\frac{R'(l)}{w(l)} \equiv \nu = \varepsilon_{L^S}^{-1} + 1 \tag{3}$$

In words, markdowns increase as the residual labor supply facing the firm is lower, i.e., as the firm has more power on its relevant labor market.

As detailed in the appendix, simple manipulations of the first order conditions of the dual cost minimization problem of the firm yield the following expression to estimate the markdown ν:

$$\nu = \left(\frac{\varepsilon_{X_k}}{\alpha_{X_k}}\right)^{-1} \cdot \frac{\varepsilon_l}{\alpha_l} = \frac{\varepsilon_l}{\varepsilon_{X_k}} \cdot \frac{\alpha_{X_k}}{\alpha_l} \tag{4}$$

where α_{X_k} and α_l represent the shares of inputs X_k and l in firm revenue, and ε_l and ε_{X_k} represent the elasticity of output with respect to each of same inputs, respectively. Hence, estimating the markdown ν boils down to (i) computing the cost shares, which are readily available from balance sheet data, and (ii) estimating the elasticities of output with respect to both inputs. Next, we discuss how we estimate these elasticities.

2.2 Estimation of the Output Elasticities

We obtain the output elasticities, ε_l and ε_{X_k}, by estimating a production function. We use expenditure on materials (m) as our flexible input (X_k). Assuming that all firms within a sector have the same production function, we can estimate the following industry-specific Cobb-Douglas production function:

$$q_{it} = \beta^l l_{it} + \beta^m m_{it} + \beta^k k_{it} + \omega_{it} + \epsilon_{it} \tag{5}$$

where lower cases denote logs, q_{it} represents the real sales of firm i in year t, l_{it} refers to the labor costs, m_{it} to the material costs, k_{it} is the real capital stock, ω_{it} is firm productivity and ϵ_{it} is the error term that captures measurement error and unanticipated productivity shocks. The challenge in obtaining consistent estimates of the output elasticities is a simultaneity bias because of the possible correlation between the firm's productivity (unobserved to the econometrician but known to the firm) and its input choice. Note that because of the Cobb Douglas assumption, the coefficients of the production function correspond to the desiderd output elasticities: $\beta^l = \varepsilon_l$ and $\beta^m = \varepsilon_{X_k}$. Following (De Loecker and Warzynski, 2012), we employ the control function approach literature pioneered by (Olley and Pakes, 1996), (Levinsohn and Petrin, 2003), and (Ackerberg et al., 2015). We assume that productivity follows a first-order Markov process and is a function of the firm's flexible inputs and capital: $\omega_{it} = h(l_{it}, m_{i,t}, k_{it})$.

The estimation involves two steps. First, we obtain estimates of the expected output to remove unanticipated productivity shocks and measurement error through a the second-order

approximation polynomial. Second, we use the law of motion for productivity to obtain the estimates by projecting productivity on its lagged value. From these steps, output elasticity can be estimated using the following moment conditions:

$$E\left(\xi_{it}(\beta)\begin{pmatrix} x_{it-1} \\ k_{it} \end{pmatrix}\right) = 0 \tag{6}$$

where x_{it-1} represents the flexible inputs labor and materials. Note that the firm chooses the flexible input, x_{it-1} after the capital stock is determined at time $t-1$ to address the critique by (Ackerberg et al., 2015).

The production function is separately estimated for each 2-digit NACE industry to obtain output elasticity for each sector for both labor input and material input. Finally, we combine the estimated elasticities and cost shares to obtain an estimate of ν as defined in equation 4.

3 Data

We use Orbis data, provided by Moody's Bureau van Dijk, for our analysis. Orbis contains information on millions of companies across the globe and its main strength lies in the availability of harmonized cross-country financial information for both private and public firms. However, the raw data requires intensive cleaning prior to estimation.

The cleaning procedure is the same as in Díez, Fan and Villegas-Sánchez (2021) and follows closely Kalemli-Özcan et al. (2015), Gopinath et al. (2017) and Gal (2013). First, the cleaning involves dealing with basic reporting mistakes (i.e., negative sales, total assets, employment, cost of employees, tangible fixed assets or liabilities; missing or zero values for the cost of materials, operating revenue, total assets and missing NACE sectoral code). Second, we implement further quality checks that verify the age of the firm, the ratio of short-term to long-term liabilities, the ratio of employees to capital, tangible fixed assets to total assets, capital to shareholder funds, and total assets to shareholder funds. Finally, we apply filters on the annual growth rates of sales, operating revenues and number of employees.

The variables used in the production function estimation (needed to obtain the elasticities β required for the markdown calculation) must be deflated. To deflate variables like revenue, wage bill, material costs, and cost of goods sold, we compiled information on value added and gross output deflators from the OECD, Eurostat and government websites, and used the ones that had better coverage across industries and time. When available we used the 2-digit NACE deflator; otherwise we used 1-digit NACE industry deflators. We followed (Inklaar and Timmer, 2011, 2014) and made PPP-adjustments when deflating the different variables

to ensure comparability of values across years and countries within industries by taking into account the differences in price levels. Capital is deflated using the WDI PPI-adjusted exchange rates. Ultimately, all variables are expressed in U.S. dollars of 2005. Again, more details are available in Díez et al. (2021).

To strengthen the representativeness and comparability of the sample across countries, we focus on the sample of firms with average employment greater or equal to 20 employees (Calligaris et al., 2018). Similarly, we drop the firms with extremely small labor- (less than 15 percent), and material-cost shares (less than 20 percent; 25 percent for goods producers).

After these steps, our sample includes over 1 million observations, from 10 countries and 11 sectors, between 2000 and 2017. Specifically, the countries that are included in the sample are Austria, Belgium, Germany, Spain, Finland, France, Italy, Norway, Portugal and Sweden.[3]. The sectors that are included are (i) agriculture, forestry, & fishing, (ii) mining & Quarrying, (iii) manufacturing, (iv) construction, (v) transportation& storage, (vi) accommodation & food Services, (vii) information & communications, (viii) finance & insurance (viiii) real estate, (x) professionals, science, & technology, and (xi) administrative support.

Table 1 shows the summary statistics of the main variables used when estimating the markdown. Our sample consists of over 1 million observations with an average annual income of $30 million (U.S. dollars of 2005). The average firm in our sample has 148 employees, pays $7.4 million for labor and $13.8 million for the material costs, and owns tangible fixed assets (proxying capital) of $7.4 million.

Table 1: Summary Statistics

cat	Turnover	Capital	MaterialCost	LaborCost	Employment
mean	30,900,000	7,404,013	13,800,000	7,443,425	148
p25	3,082,000	225,014	1,133,000	920,099	27
p50	6,134,543	781,445	2,514,222	1,663,310	41
p75	14,300,000	2,711,000	6,287,914	3,605,000	82
N	1,180,675	1,180,675	1,180,675	1,180,675	994,934

Notes: Monetary variables are expressed in U.S. dollars of year 2005. Turnover is operating revenue; Capital refers to tangible fixed assets; MaterialCost is the cost of materials. LaborCost is the cost of labor for a firm; Employment is the number of employees. Source: Orbis.

[3]For Austria, Germany, Norway, Portugal and Sweden, the sample starts in 2006. However, our results are robust to limiting the sample to a strongly balanced panel (i.e., excluding these countries)

4 Labor Market Power in Europe

In this section, we first characterize the overall situation of labor market power in Europe. Next, we focus on recent markdown dynamics, emphasizing the differences across different central tendency measures as well as across countries and sectors.

4.1 Overview of Markdowns

We begin by providing a snapshot at our estimated markdowns. Table 2 shows the median, mean, inter-quartile range (IQR), and standard deviations for the entire sample and across industries. There are several things worth noting from the table. First, the median firm has a markdown of 1.58, which implies that the median firm has market power in the labor market—i.e., its residual labor supply elasticity is finite. In contrast, in a perfectly competitive labor market, the firm is a ”wage-taker” facing an infinitely elastic labor supply. Instead, in our sample, the median markdown of 1.58 implies that the median firm is only paying around 60 (=1/1.58) percent of marginal product of labor. Second, the IQR and standard deviations are large suggesting substantial heterogeneity across firms within sectors. Third, labor market power seems to be pervasive in all industries, although with sizable differences across sectors, with markdowns in accommodation and food services being the lowest while those on mining being the largest.[4]

The values presented in the table, while slightly higher, are broadly in line those found by Yeh et al. (2022), that find a median of 1.36 (although their data goes back to the 1970s when markdowns were smaller). Further, our findings are also within the range of estimates found in the meta-analysis by Sokolova and Sorensen (2021). Taken at face value, these findings suggest that labor market power is generalized throughout Europe. However, as we show next, the narrative changes significantly when moving from this snapshot to the dynamics of markdowns.

[4]It is worth noting that markdowns measure the *marginal* wedges, not overall payment levels. Thus, for instance, these findings should not be interpreted as workers in hotels and restaurants being necessarily better off than miners.

Table 2: Summary Statistics of Firm-Level Markdowns

NACE1	Median	Mean	IQR_{75-25}	SD
Agr. For.&Fish.	1.56	1.82	1.34	1
Mining&Qua.	2.23	2.43	1.48	1.1
Manufacturing.	1.65	1.81	1.2	.88
Construction	1.69	1.99	1.31	1.08
Trans.&Sto.	1.24	1.7	1.19	1.25
Accom.&FoodServ.	1.18	1.35	.62	.68
Info.&Comm.	1.78	2.25	1.82	1.49
Fin.&Ins.	2	2.27	1.8	1.22
RealEstate	2.04	2.39	1.97	1.38
Prof.Sci&Tech	1.8	2.17	1.78	1.35
Admin.&SupportServ.	1.64	2.06	1.54	1.37
All	1.58	1.83	1.24	1.01
Num. Obs	1,180,675			

Notes: Markdown estimates using ORBIS between 2000 and 2017 for 10 European Countries. "Median", "Mean", "IQR_{75-25}", and "SD" stand for the median, (unweighted) mean, and interquartile range, and standard deviations of the markdown distribution. Source: authors' calculations based on Orbis data.

4.2 Markdown Dynamics Across Central Tendency Measures

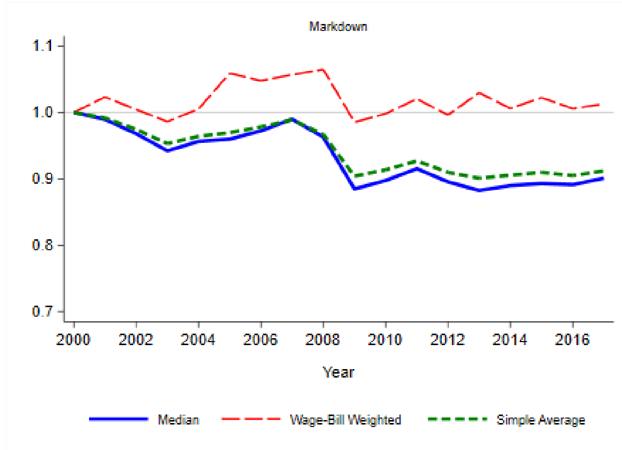
Next, we focus on the evolution of markdowns. Figure 1 plots the dynamics for different measures of central tendency, normalizing the values to 2000=1 to emphasize the changes. Zooming in first on the wage-bill weighted average we find a small increase of 1.3 percent (red line). This result also holds true when we use alternative weights such as revenue and employment (see Appendix Figure 8). This increase in markdowns is in line with findings on other studies.

However, if we focus instead on the evolution of other measures of central tendency we find a very different picture. Specifically, we find that the median and the simple average markdowns actually *decreased* by about 10 percent (blue and green lines). Similar trends are observed for other percentiles.[5].

The stark difference in dynamics across measures suggests the presence of a opposing forces at work, with compositional effects playing a large role in explaining dynamics—as larger firms (i.e., higher wage bills) experienced an increase in labor market power. We explore more formally this possibility in Section 5.3.

[5]In the appendix, we also show that our results, across measures, are robust to accounting for potential labor adjustment costs. See Appendix section A.3

Figure 1: Markdown Trends by Different Measures of Central Tendency



Note: Figure 1 plots the median revenue (employment) share in local market (country × Nace2 × year) among the firms in each markdown decile. Data are from Orbis.

4.3 Markdowns by Country and by Sector

After having established some stylized facts about the overall markdown distribution, we now exploit the granularity of our data to look into sectors and countries.

We begin by distinguishing between the markdowns of firms in goods-producing sectors from those in services sectors in Figure 2. There are two things worth noting. First, looking at the weighted averages, it is apparent that there was in increase in services (blue dashed line) while there was a very small decrease in goods, suggesting that the overall increase mention in the previous section is driven by firms from services sectors. Second, when looking at median markdowns, we also observe a decline in goods—but we also observe an even larger decline in services. Both facts, imply that there is greater variability across service- than goods-producing firms.[6]

Next, we present more granular results by looking at markdowns at the 1-digit sector-by-country level. Each cell in Figure 3 shows the change in weighted average markdowns by sector-country, with red colors indicating an increase and blue colors indicating a decrease. When looking across countries, Spain, Italy, and Norway have seen a decline in markdowns across almost all sectors, while increases were more common in Belgium, Finland, and France. Looking across sectors, 'accommodation and food services' sector have seen a decline across most countries while increases were relatively more common for other sectors like 'transportation and storage.' This high degree heterogeneity highlights the importance of looking across countries and sectors to get a complete picture of the evolution of labor market power.

[6] We also find that median markdowns decreased in all countries except for Belgium and Germany where there was a slight increase.

Figure 2: Markdown in Goods vs Service Sector

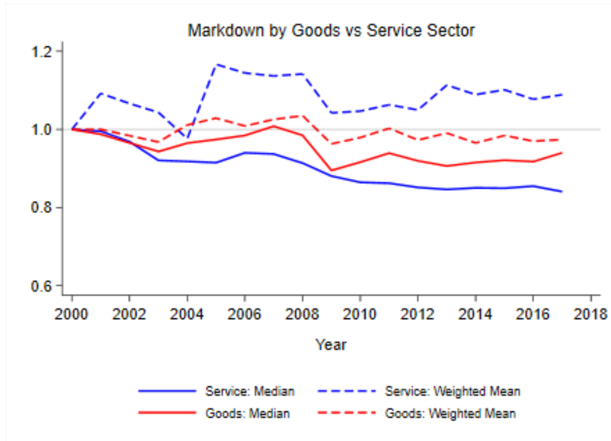
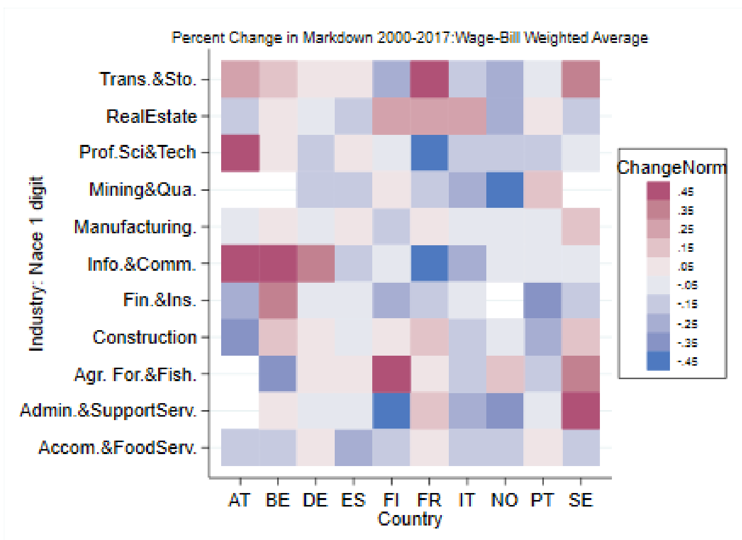


Figure 3: Change in Markdown: Heatmap by Country × Industry



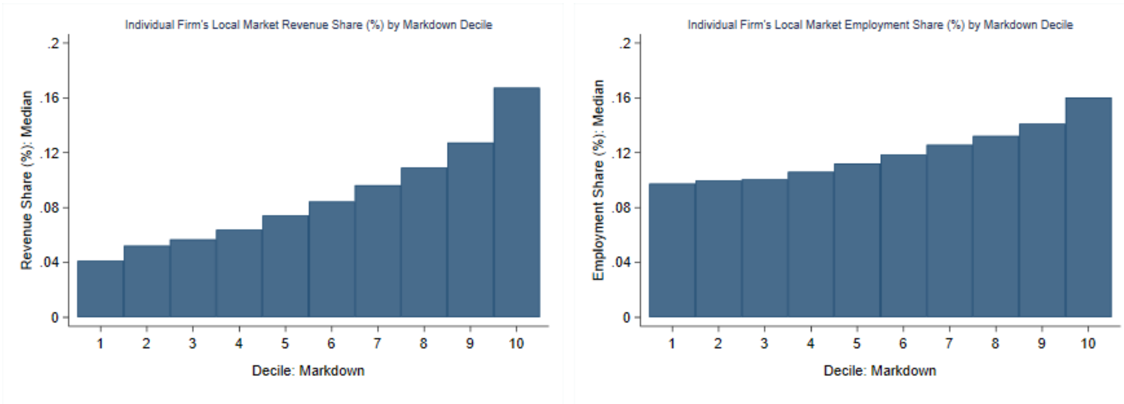
Note: Figure 3 shows the changes of markdown over time for each country × year cell.

5 Firms Driving Markdown Dynamics

Our previous results suggest the existence of substantial heterogeneity across firms, with some firms driving the increase in the aggregate weighted average while most firms saw a decline in markups (as manifested by the decreases in median and 75 percentile). In this section we zoom into these cross-firm differences, emphasizing the role of high-markdown firms and quantifying the role of resource reallocation towards large firms.

Figure 4: Markdown: Labor and Output Markets

(a) Revenue Share (b) Employment Share



Note: The figure shows the median revenue (employment) share in local market (country × Nace2 × year) among the firms in each markdown decile. Data are from Orbis.

5.1 Markdowns and Local Markets Footprint

We begin by exploring whether high markdown firms are quantitatively relevant in their local output and labor market. To this end, we sort firms into deciles (according to their average markdown) and cross-tabulate this against their revenue and employment shares in their local market, where local market is narrowly defined at the industry (NACE 2 digits) × country × year level. Within each decile, we calculate the median revenue and employment shares.

Figure 4a indicates that median revenue share is increasing in markdowns. In other words, firms with higher markdown have a higher median revenue share. Similarly, Figure 4b suggests that firms in higher markdown deciles have higher median employment share in their local market. These finding suggest that firms with higher markdown have presence in their local labor market, both in terms of output (revenue share) and input (employment share).

5.2 High- and Low-Markdown firms

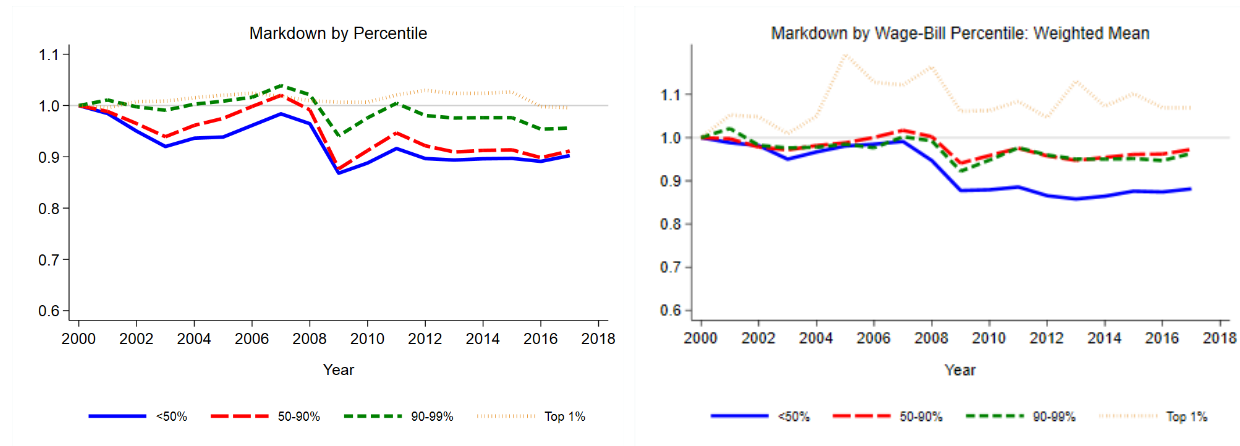
In this section, we analyze the markdown dynamics, separately for different percentiles of the firm markdown-average distribution. Specifically, as before, we compute the average markdown for each firm in our sample and we sort them into four groups: below the median, between the 50th and the 90th percentiles, between the 90th and 99th percentiles, and the top-1 percentile. We then compute the median markdown prevailing within each group.

The results reported in Figure 5a. It is clear that the majority of firms experienced

Figure 5: Markdown Trends by Percentiles

(a) By Markdown Percentiles

(b) By Wage-Bill Percentile



Note: Figure 5a plots the evolution of markdown by mean markdown percentiles. First, mean markdown is calculated at the firm level and then sorted into different bins (<50%, 50-90%, 90-99%, and Top 1%). Within the group, the evolution of the median markdown is plotted. Figure 5b plots the evolution of markdown by wage-bill percentiles. Within each bin, the evolution of the wage-bill weighted average is plotted. Data are from Orbis.

a decline in labor market power. The strongest decline took place among firms in the bottom half of the average markdown distribution for which the median markdown decline by approximately 10 percent. Interestingly, firms between the median and the 90th percentile showed almost the exact decline. Firms between the 90th and the 99th percentile saw a decline half as large (around 5 percent). In contrast, firms in the top percentile did not decrease their markdowns. These results suggest that high-markup firms' markdown trend diverges from the trends of all other firms, being the only group of firms that avoided reducing markdowns.[7]

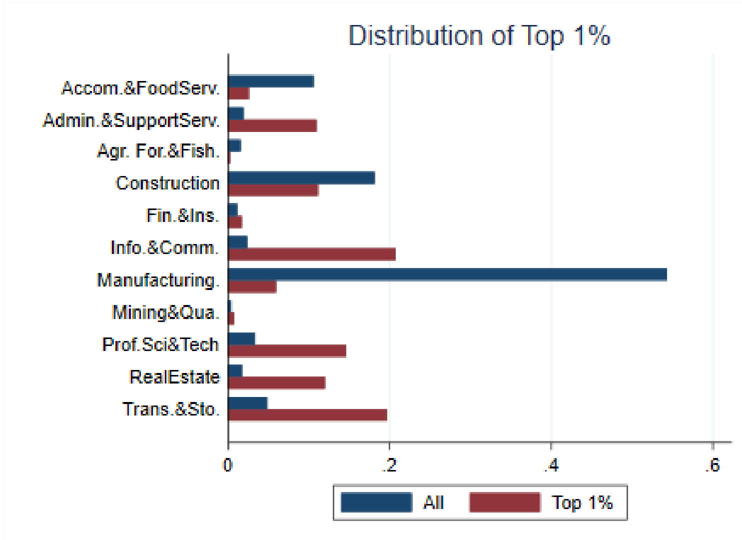
Table 3: Summary Statistics by Mean Markdown Percentile

mean_pct	Turnover	Capital	MaterialCost	LaborCost	Employment	Listed (%)
bottom50	2,0000,000	5,107,668	6,854,152	6,221,264	129	.42
50-90	39,100,000	9,465,817	18,300,000	8,372,503	159	.53
90-99	52,100,000	10,200,000	30,300,000	9,608,891	184	.47
Top1	91,500,000	11,900,000	62,300,000	15,500,000	291	.6

Notes: Monetary variables are expressed in U.S. dollars of year 2005. Turnover is operating revenue; Capital refers to tangible fixed assets; MaterialCost is the cost of materials. LaborCost is the wage bill; Employment is the number of employees. The values are mean values of corresponding percentile brackets. Source: authors' calculations based on Orbis.

[7] Figure 5b conducts a complementary exercise by sorting firms according to their average wage bills. Once again, we observe declines in all groups except for the 1 percent that actually registers an increase—suggesting that larger firms increased their average markdown over time. Section 5.3 formalizes this intuition.

Figure 6: Top 1 % Markdown Firms: Distribution Across Sectors



Note: Figure 6 plots the Top 1% distribution of markdown across sectors. Data are from Orbis.

Next, we zoom into this top-1 percent of firms, that have divergent markdown trends and are the main driving force behind the increase in overall (weighted average) markdowns. In Table 3 we present some basic statistics for each of the groups from Figure 5. From the table it is clear that these firms with the highest average markdown are the largest firms across all size metrics considered (e.g., turnover revenue, capital, employment). Further, these firms are also more likely to be listed firms than firms from the other groups. Figure 6 shows the distribution of top-1 percent firms across sectors, along with the entire distribution of firms. From the figure it is clear that top-1 percent firms are relatively more concentrated among some service sectors (like 'Information and Communications' or 'Professional, Scientific and Technical Activities') than in goods sectors (e.g., manufacturing) or other service sectors ('accommodation and food services')—which is aligned with our previous findings from Section 4.3.

These diverse dynamics across the markdown distribution, paired with the documented increase in *weighted* markdowns, suggests that reallocation may have played a crucial role in avoiding a decline in markdowns. The next section looks into it via a formal decomposition.

5.3 Melitz-Polanec Decomposition

In this section we quantify the relative contributions of different factos to the change in (aggregate) weighted average markdown changes. Specifically, we follow the decomposition proposed in Melitz and Polanec (2015) and break down the change in aggregate weighted average markdown into the contributions of incumbent, entering, exiting firms. Further, the

analysis also decomposes the changes in each of these three groups into a "within component" (i.e., how much of change is driven by the increase in average firm markdowns, keeping size fixed) and a "reallocation component" (i.e., how much of the change is driven by high-markdown firms increasing their size—wage bills—keeping markdowns fixed). See Díez et al. (2021) for more details on the computation.

We look at the cumulative change in the weighted average markdown between 2000 and 2017. The surviving firms are the ones that were present in both 2000 and 2017. The entering firms are those that were not in the sample in 2000 but appear in the 2017 sample. Exiting firms are those that were present in the sample in 2000 but no longer were present in 2017.

Figure 7 reports the decomposition results. The weighted average markdown increased by 1.26 percent between 2000 and 2017 (black '1. Total change' bar).

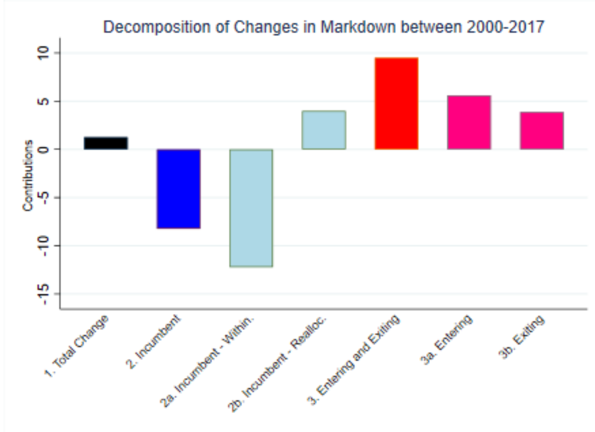
The total change among incumbent firms was negative, at -8.2 percent (dark blue '2. Incumbent' bar). However, this number masks a sharp discrepancy. Indeed, this drop is entirely driven by the within-firm component (light blue "2a. Incumbent - Within" bar), measured as the unweighted simple mean change in the markdown of incumbent firms between 2000 and 2017, at -12.2 percent. Instead, the reallocation effect ("Incumbent - Realloc"), measured as the change in the covariance between firm markdown and size was positive, at 4 percent. This suggests that within the sample of incumbent firms, the covariance between markdown and size has increased: high-markdowns firms tend to become larger. The extensive margin also contributed positively to the increase in weighted average markdowns. Entering firms (pink "3a. Entering" bar) had an increase of 5.62 percent while the exits of firms (pink "3b. Exiting" bar) contributed with a 3.89 percent increase. In other words, entering firms had a higher than average markdown, while exiting firms a lower than average markdown.

In sum, this dynamic decomposition analysis suggests that the weighted mean increase in markdown between 2000 and 2017 can be explained by reallocation across firms toward higher markdown firms gaining higher wage bill shares, jointly with the entry-exit dynamics (and both effects offsetting the decline from the within-firm component).

6 Conclusions

In this paper we present new evidence on the recent evolution of labor market power in Europe. We use detailed firm-level data from 10 European countries to estimate markdowns (our measure of market power, defined as the ratio of marginal revenue of labor to wages) and find evidence of firm monopsony power in labor markets. Further, we also find that weighted average markdowns increased 1.3% over 2000-2017.

Figure 7: Dynamic Decomposition with Firm Entry and Exit



Note: Panel A plots the median, the 25th and the 75th percentile of the distribution of markdowns in the sample between 2000 and 2017. Panel B plots the median, simple average, and wage-bill-weighted average markdown. Panel C shows the decomposition exercise: notice that bars 3 and 4 sum to bar 2; bar 1 is the sum of bar 2, 5 and 6. Figure panel D shows markdowns of firms with various average levels of markdowns. Specifically, firms are assigned to a percentile based on their mean markdown over the sample. Panel E plots the markdown of the average firm, weighted by wage bills, operating in the services and good sector respectively, over time. Data are from Orbis.

However, there is substantial cross-firm heterogeneity underlying this average figure. Specifically, we show that the median actually decreased around 10% over the same period. These facts suggest the existence of divergent markdown paths—the vast majority of firms saw markdown declines, with the exception of a few top firms. These high-markdown firms are large and have a sizable footprint in their local product and labor markets. Consistent with these findings, a decomposition of the markdown increase shows that while within-firm markdowns decreased, this was offset by strong reallocation effects towards high-markdown firms.

These findings highlight the importance of carefully studying the degree of competition in input markets. Further, the differences we find relative to previous work in the literature suggest that is equally important to expand the research to other countries and sectors in order to think about appropriate policy responses to market power outcomes, bearing in mind the substantial heterogeneity presented in the paper.

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A Appendix

A.1 Markdowns as a function of estimable quantities

To explain how balance sheet data can be used to estimate the markdown, it is more convenient to look at the dual firm cost minimization problem. Consider now a firm whose production function depends on a vector of inputs $\mathbf{X} = [X_1, X_2 \dots X_n]$ (with associated vector of prices $\mathbf{V}_X$), labor input l with price $w(l)$, subject to the contraint that the firm produced at least $\bar{Q}$:

$$\min \mathbf{V}'_X \mathbf{X} + w(l)l \quad s.t. \quad Q(\mathbf{X}, l) > \bar{Q}$$

The first order conditions for each input $X_k, k \in \{1 \dots n\}$–for which the firm is assumed to be a price taker–and labor are

$$V_k = \lambda Q^{X_k} \tag{7}$$

$$w'(l)l + w(l) = \lambda Q^l \tag{8}$$

where Q^x indicates the partial derivative of the function $Q(\mathbf{X}, l)$ with respect to its argument x and λ is the Lagrange multiplier.

Equation (7) can be rearranged to

$$\frac{V_k X_k}{PQ} = \frac{\lambda}{P} \frac{Q^{X_k} X_k}{Q}. \tag{9}$$

Since λ captures the marginal cost of producing one extra unit of Q, the markup of the firm can be defined as $\mu = P/\lambda$. Therefore, μ can be expressed:

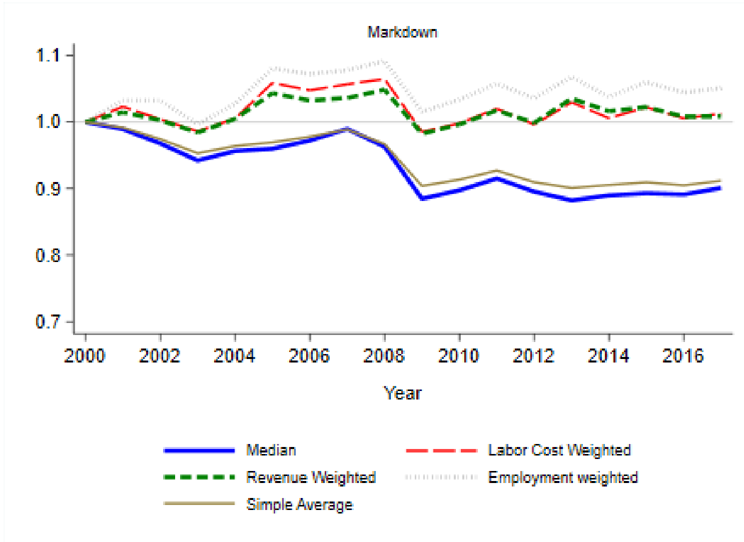
$$\mu = \varepsilon_{X_k} / \alpha_{X_k} \tag{10}$$

where ε_{X_k} is the elasticity of output with respect to the flexible input X_k, which needs to be estimated, and α_{X_k} is the cost share of input X_k of total value added, which can be readily computed from balance sheet data.

Similarly, equation (8) can be rearranged to

Figure 8: Markdown Trend

Median, Unweighted, Labor-Cost Weighted, Revenue-Weighted, Employment-Weighted Markdown



Note: Figure plots markdown by different weighting schemes.

$$\nu \equiv \tag{11}$$

$$\frac{w'(l)l}{w(l)} + 1 = \frac{\lambda}{P}\frac{Q^l l}{Q}\frac{PQ}{w(l)l} \tag{12}$$

$$\equiv \mu^{-1}\frac{\varepsilon_l}{\alpha_l} \tag{13}$$

and combining equation (10) with equation (13) yields the following expression for ν:

$$\nu = \left(\frac{\varepsilon_{X_k}}{\alpha_{X_k}}\right)^{-1} \cdot \frac{\varepsilon_l}{\alpha_l} = \frac{\varepsilon_l}{\varepsilon_{X_k}} \cdot \frac{\alpha_{X_k}}{\alpha_l} \tag{14}$$

which is also equation 4 in the main text.

A.2 Different Weighting Schemes

Figure plots mean markdown by different weighting schemes. Average markdown weighted by wage bills, revenues, and number of employments, all show increase in markdowns at 1.27, 0.89 and 5.1 percent increases, respectively.

A.3 Robustness to the presence of labor adjustment costs

Our baseline estimation of markdown relies on the assumptions that materials and labor are both flexible and do not incur adjustment costs. Presence of labor adjustment costs threaten this assumption. Following Yeh et al. (2022), we assume labor adjustment costs to have the following quadratic form:

$$\Phi(l, l_{-1}) = \frac{\gamma}{2} l \left(\frac{l - l_{-1}}{l_{-1}} \right)$$

where l and l_{-1} are the labor in the current and last period, respectively and γ is the adjustment cost parameter. As in Yeh et al. (2022), we follow Hall (2004) and set $\gamma = 0.185$. The resulting markdown with labor adjustment cost is as follows:

$$\nu_{adj} = \frac{\nu - \gamma \cdot [g_l(1 + g_l) - \beta g_{l'}(1 + g_{l'})(1 + g_{sw'})]}{1 + \frac{\gamma}{2g_l^2}} \tag{15}$$

where $g_l = \frac{l - l_{-1}}{l_{-1}}$ and $g_{l'} = \frac{l' - l}{l}$ are a firm's present and future labor growth rate and $g_{sw'} = \frac{w(l')l' - w(l)l}{w(l)l}$ is a firm's future wage growth.

We then compute the mean future wage growth and current and future labor growth rates and plug them into equation 15 for each year, and the discount factor $\beta = 1$.

We then try two different labor adjustment parameter values based on the idea that labor adjustment costs may be higher in Europe than in the US. Specifically, we increase the value of γ from 0.185 up to1. This amounts to imposing that the labor adjustment cost parameter is more than five times larger in Europe than the US.

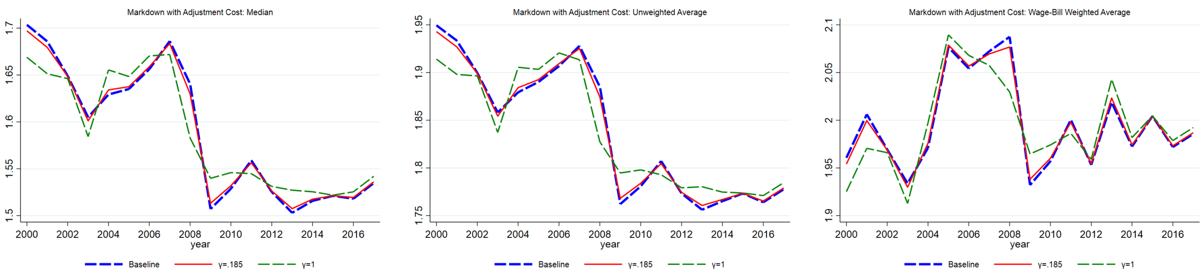
Figure 9 plots the evolution of median, unweighted average, and wage-bill weighted average markdown with labor adjustment costs with respect to the baseline markdown without labor adjustment costs. While adjustment costs are responsible for some of the volatility in markdowns, they do not change our main result of the markdown trends: median and unweighted average markdowns decreased while the wage-bill weighted average markdown slightly increased during the sample period.

A.4 Age and Size

We also study how markdown is associated with firms age and employment size. For the US, Yeh et al. (2022) document that markdown is increasing in (employment) size and ages for the firms in manufacturing sector. In this section, we examine whether this result remains true for different set of countries and industries. As Haltiwanger et al. (2013) stress the importance of controlling for age when assessing size effects as they are highly correlated

Figure 9: Markdown with Labor Adjustment Cost

(a) Median (b) Unweighted Average (c) Wage-Bill Weighted Average



Note: The figures plot the evolution of median/unweighted average/weighted average markdown with labor adjustment costs. Adjustment costs parameters are set as $\gamma = 0.18$ or $\gamma = 1$. Since we use dynamic labor and wage growth rates, we use the mean labor and wage growth rates for 2001 (2016) to input the adjusted markdown in 2000 (2017). Data are from Orbis.

with one another, our regression specification is as follows:

$$\nu_{it} = \beta_0 + \sum_{j=1}^{S} \beta_j^{size} \cdot 1_{s_{it} \in S_j} + \sum_{j=1}^{A} \beta_j^{age} \cdot 1_{age_{it} \in A_j} + X' \cdot \beta_x + \epsilon_{it} \tag{16}$$

where X_{it} contains industry, country, year fixed effects. Employment size dummies are defined as deciles based on the firm $i's$ employment share of its local market (NAICS2 $\times$ Country $\times$ Year). We also categorize firms' age into 10 groups.[8]

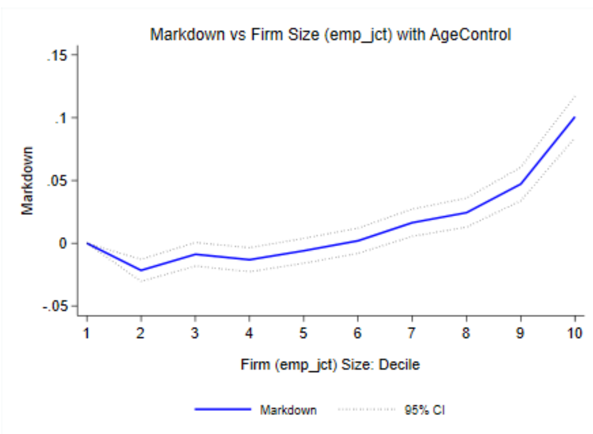
Figure 10 plots the regression coefficients, β_j^{size} and β_j^{age} from equation 16. Figure 10a shows that markdown is increasing in size (employment share). The firm in the top decile of the size distribution, on average, have markdown that is roughly 10 percent higher than that of the firm in the smallest decile.

Markdown seems to have a inverted-U shape relationship with the age. Firms tend to have a higher markdown as they age, and they tend to peak in its markdown level at around 13-15 years after its birth. It then declines further, although the differences at the older groups are not statistically significant.

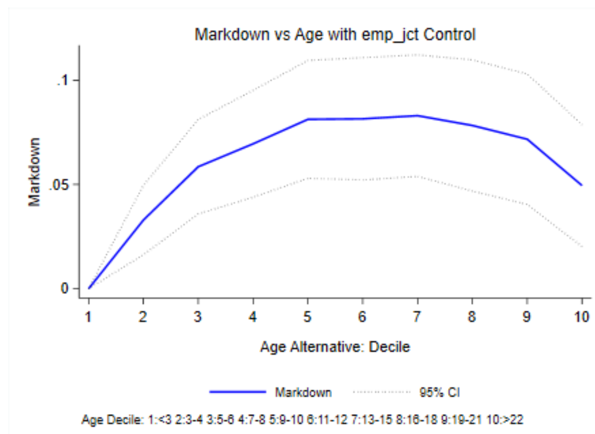
[8]While we use 10 different age group categories, (Yeh et al., 2022) use 8 age groups. For comparison purpose, we use the same age groups for up to 7th age group. Specifically, we divide firms into 10 age groups of: 1) less than 3 years old, 2) 3-4 years old, 3) 5-6 years old, 4) 9-10 years old, 5) 11-12, 7) 13-15, 8) 16-18, 9) 19-21, and 10) 22 years old and above.

Figure 10: Markdown: Firm Size and Age

(a) Markdown and Employment Size



(b) Markdown and Age



Note: The chart reports the coefficient of a regression of markdowns different deciles of firm size and age. Firm size is defined as the employment share of the firm in its sector-by-country cell. Firm age is taken unconditionally. In the size regression, age is controlled for, and in the age regression size is controlled for. In both cases, the bottom decile is the omitted category. Data are from Orbis.