IWH
Halle Institute for Economic Research
Member of the Leibniz Association

Discussion Papers

No. 1
January 2023

Do Larger Firms Exert More Market Power? Markups and Markdowns along the Size Distribution

Matthias Mertens, Bernardo Mottironi

Authors

Matthias Mertens
Halle Institute for Economic Research (IWH) – Member of the Leibniz Association, Department of Structural Change and Productivity, and The Competitiveness Research Network (CompNet)
E-mail: matthias.mertens@iwh-halle.de
Tel +49 345 7753 707

Bernardo Mottironi
London School of Economics and Political Science (LSE)
E-mail: b.mottironi@lse.ac.uk

The responsibility for discussion papers lies solely with the individual authors. The views expressed herein do not necessarily represent those of IWH. The papers represent preliminary work and are circulated to encourage discussion with the authors. Citation of the discussion papers should account for their provisional character; a revised version may be available directly from the authors.

Comments and suggestions on the methods and results presented are welcome.

IWH Discussion Papers are indexed in RePEc-EconPapers and in ECONIS.

Editor

Halle Institute for Economic Research (IWH) – Member of the Leibniz Association

Address: Kleine Maerkerstrasse 8
D-06108 Halle (Saale), Germany
Postal Address: P.O. Box 11 03 61
D-06017 Halle (Saale), Germany

Tel +49 345 7753 60
Fax +49 345 7753 820

www.iwh-halle.de

ISSN 2194-2188

Do Larger Firms Exert More Market Power? Markups and Markdowns along the Size Distribution*

First version: January 5, 2023
This version: September 18, 2023

Abstract

Several models posit a positive cross-sectional correlation between markups and firm size, which characterizes misallocation, factor shares, and gains from trade. Accounting for labor market power in markup estimation, we find instead that larger firms have lower product markups but higher wage markdowns. The negative markup-size correlation turns positive when conditioning on markdowns, suggesting interactions between product and labor market power. Our findings are robust to common criticism (e.g., price bias, non-neutral technology) and hold across 19 European countries. We discuss possible mechanisms and resulting implications, highlighting the importance of studying input and output market power in a unified framework.

Keywords: firm size, markdowns, market power, markups

JEL classification: J42, L11, L13, L25

* We thank Maarten De Ridder, Filippo di Mauro, Alan Manning, Devesh Raval, John Van Reenen, and seminar participants at the LSE, Kent University, and EARIE conference for insightful comments and suggestions. We are grateful to Michael Rößner and Denise Henker for their support on the data. We thank all data-providing institutions within the CompNet network.

1 Introduction

Do larger firms have higher markups? If we consult modern economic theories and standard models alike, the answer is almost always "yes".[1] This is not surprising. Intuitively, larger firms have a more dominant market position and could thus more easily influence prices. Formally, also Marshall's second law of demand states that the price elasticity of demand falls with the quantity consumed (Marshall (1936)).

The cross-sectional correlation between markups and firm size is a key outcome in many economic models featuring firm-level markup heterogeneity. Among others, this correlation characterizes misallocation in the economy, aggregate profit shares (Autor et al. (2020)), optimal policies (e.g., Edmond et al. (2023)), and potential gains from competition (Dhingra & Morrow (2019), Arkolakis et al. (2019), Mayer et al. (2021)). It is therefore key to understand whether the data can support that larger firms charge higher markups.

To test this hypothesis, we follow a dual approach. Firstly, we estimate a rich translog production function on a unique sample of German manufacturing firms, whose prices and quantities are observed, to obtain output elasticities which do not suffer from the "price bias".[2] From that, we derive a clean measure of markups using the "production approach" of De Loecker & Warzynski (2012) and find a striking

[1] This holds for the Cournot model as well as for several recent contributions, e.g., Atkeson & Burstein (2008), Melitz & Ottaviano (2008), Edmond et al. (2015, 2023), Parenti (2018), Boar & Midrigan (2019), De Loecker et al. (2020), Burstein et al. (2020), Peters (2020), Hubmer & Restrepo (2022), Bao et al. (2022), Macedoni & Weinberger (2022).

[2] For discussions on the price bias in production function estimation, see De Loecker et al. (2016), Bond et al. (2021), and De Ridder et al. (2022).

result: contrary to most existing theories, larger firms charge *lower* markups within narrowly defined industries and product markets.

Secondly, we exploit that markups can be compared across firms within industries without estimating output elasticities, if the production function is assumed to be Cobb-Douglas. Using this simplified yet widely applied specification, we test the markup-size relationship using data on 19 European countries covering almost all economic sectors and confirm our previous result for every country examined.

The production approach is widely used to measure markups, but its caveats generated some fair criticism.[3] We carefully examine the known issues of this methodology and show that none of them can rationalize the negative relationship between markups and size.

As our findings seem to contradict existing work, we discuss two potential reasons why previous studies found different results regarding the markup-size correlation.[4] Firstly, many studies estimate markup expressions that jointly capture firms' product markups and wage markdowns.[5] Particularly, if researchers rely on firms' labor input decisions to estimate markups, their results will be biased whenever labor markets are not perfectly competitive. Relying on such markup expressions makes it unclear

---

[3] E.g., Bond et al. (2021), Hashemi et al. (2022), Raval (2023a).

[4] For instance, De Loecker & Warzynski (2012) report a positive association between markups and export status in Slovenia, Autor et al. (2020) estimate a positive correlation between markups and firm size for the U.S., and Bellone et al. (2016) report that markups are increasing with firm productivity in France.

[5] Markdowns are defined as the marginal revenue product of labor (MRPL) over labor costs per worker. Following the literature, we interpret them as a measure of labor market power. They can be below or above unity, because of, respectively, monopsony power or rent-sharing.

whether studied associations between market power and firm size result from firms' product or labor market power. In this study, we carefully differentiate the two market power types using recent methodological advances building upon Dobbelaere & Mairesse (2013). We show that the adjustment in markup measurement can fully explain why previous work found a positive association between markups and firm size, because markdowns grow in firm size.[6]

Secondly, the negative correlations between firm size and markups turn positive after conditioning on wage markdowns. This results from a negative correlation between product markups and wage markdowns that we document in all countries of our data, suggesting the presence of interactions between product and labor market power. The extent to which such market power interactions are relevant is determined by the underlying features of labor markets and modes of competition. Cross-country heterogeneity in such market features can affect the relationship between markups and firm size, which might be particularly relevant when comparing our findings to the US.

Importantly, we show that our findings do not contradict Marshall's second law of demand (i.e., larger firms face a less elastic demand), which would be the usual explanation for a negative correlation between markups and firm size (Zhelobodko

[6] Recently, also Raval (2023a, 2023b) highlighted the relevance of measurement error in markups. He focuses on unobserved labor augmenting productivity. We make a similar point but show that our results are robust to the correction for labor augmenting productivity suggested by Raval (2023b). Instead, we highlight unobserved labor market power as a key measurement issue in previous work.

et al. (2012), Dhingra & Morrow (2019)). As controlling for markdowns restores the positive size-markup correlation, our evidence rather suggests that markups fall with firm size because of strategic interactions between labor and product market power.

In particular, we show that if workers' bargaining power is a decreasing function of firm size, firms have an incentive to cut prices and expand by charging lower markups than implied by the elasticity of demand. This trade-off between rent-seeking in input and output markets provides a possible mechanisms that can rationalize why larger firms have lower markups without violating Marshall's second law of demand. An important implication of this mechanism is that the demand elasticity alone is not sufficient to identify markups.

Our results provide two additional key insights. First, existing models featuring a positive markup-size correlation might draw potentially wrong conclusions on how markup heterogeneity affects economic outcomes. For instance, because the correlations between markups, markdowns, and firm size jointly affect i) the extent to which large firms over- or underproduce, and ii) the type of optimal policies to address distortions (product vs. labor market policies). Second, the negative correlation between product markups and wage markdowns points to interactions between firms' product and labor market power with potentially large implications. For instance, if firms share product market rents with workers, rising markups will not necessarily decrease wages and labor shares as argued in recent work (e.g., De Loecker et al. (2020), Deb et al. (2022)). Our study therefore sheds new light on how markup heterogeneity shapes economic outcomes and calls for considering interactions between labor and product market power in future work.[7]

The remainder proceeds as follows: Section 2 presents the data. Section 3 explains the estimation of markups and markdowns. Section 4 presents our findings. Section 5 considers the main threats to our identification and compares our results with other studies. Section 6 discusses possible mechanisms and key implications. Section 7 concludes.

2 Data

2.1 German manufacturing sector firm data

The first part of the analysis is performed using rich firm-product-level panel data for the German manufacturing sector (1995-2016), supplied by the statistical offices of Germany.[8] The data contains information on firms' employment, investment, revenue, and, most importantly, product quantities and prices at a ten-digit product classification.[9] Observing firm-specific prices and output quantities allows us to estimate a quantity-based production model of firms and to address the price bias when estimating markups.

[7] Recent work studies the role of labor market power, yet, without discussing interactions between firms' product and labor market power (e.g., Jha & Rodriguez-Lopez (2021), Macedoni (2021), Berger et al. (2022a, 2022b)).

[8] Data source: RDC of the Federal Statistical Office and Statistical Offices of the Federal States, DOI: 10.21242/42131.2017.00.03.1.1.0, 10.21242/42221.2018.00.01.1.1.0, and 10.21242/42111.2018.00.01.1.1.0.

[9] The product classification defines about 6,000 products. Examples of product categories are: "Workwear – Long trousers for men, cotton", "Tin sheets and tapes, thicker than 0.2mm", "Passenger cars, petrol engine ≤ 1,000 cm^3"

The statistical offices collect this data only for firms with at least 20 employees. Furthermore, some variables are only collected for a representative and periodically rotating firm sample, covering 40% of all manufacturing firms with at least 20 employees. We focus on this 40% sample as it contains necessary information for estimating markups. Online Appendix A.1 provides further details on the German data.[10]

2.2 European cross-country data

To provide further European evidence, we use the CompNet data that we collected and published together with the CompNet team and several European national statistical institutes and central banks. The CompNet data contains aggregated firm-level information. The data is collected from harmonized data collection protocols that run over administrative and representative firm-level databases of 19 European national statistical institutes and central banks. These protocols calculate various firm-level performance measures, including firms' markups, wage markdowns, and size, aggregated at the two-digit industry level.

Importantly, the data provides "joint distributions" which, among others, summarize markups by firm size quintiles. These joint distributions are key for our analysis. The

[10] We clean the data from top and bottom two percent outliers with respect to revenue over labor, capital, intermediate input expenditures, and labor costs. We eliminate quantity and price information for products' displaying a price deviation from the average product price located in the top and bottom one percent tails. Our results are robust to alternative cleaning routines.

underlying firm population is truncated at a 20 employees cut-off.[11] To ensure representativeness, variables are weighted by firm population weights.

TABLE 1

COMPNET DATA, COVERAGE INFORMATION

Country	Years (1)	Excluded sectors (2)	Median firms' number of employees (4)
Belgium	2000-2018	None	36.42
Croatia	2002-2019	None	39.00
Czech Republic	2005-2019	None	41.40
Denmark	2001-2016	Real estate activities and ICT	36.11
Finland	1999-2019	Real estate activities	38.38
France	2004-2016	None	37.60
Germany*	2001-2018	None	43.22
Hungary	2003-2019	None	38.18
Italy	2006-2018	Real estate activities	35.00
Lithuania	2000-2019	None	38.60
Netherlands	2007-2018	Real estate activities	39.62
Poland	2002-2019	None	44.56
Portugal	2004-2018	None	35.60
Romania	2007-2019	Real estate activities	38.46
Slovakia	2000-2019	None	48.55
Slovenia	2002-2019	None	41.95
Spain	2008-2019	None	34.00
Sweden	2003-2019	None	37.47
Switzerland	2009-2018	None	44.20

Notes: Table 1 reports statistics on the CompNet data. Column (1) reports the covered years, column (2) lists the one-digit sectors excluded from the underlying firm-level dataset, and column 3 reports associated averages of the firm-level median number of employees. All statistics refer to firms with at least 20 employees.
* Sectoral coverage varies over time in Germany. For 2005-2018, all sectors are covered.

There are multiple vintages of the data that differ in terms of coverage and variables. We use the 8th vintage CompNet data. It covers the years 1999-2019 and the NACE rev. 2 industries 10-33 (manufacturing), 41-43 (construction), 45-47 (wholesale/retail trade and repair of motor vehicles and motorcycles), 49-53 (transportation/storage), 55-56 (accommodation/food services), 58-63 (ICT), 68 (real

[11] For a smaller set of countries, the data is also available without a size cut-off. All results hold for the data without the size cut-off.

estate), 69-75 (professional/scientific/technical activities), and 77-82 (administrative/support service activities).

Table 1 presents the yearly and sectoral coverage of the CompNet data for each country. Online Appendix A.2 provides details on data access. For further information on the data, we refer to CompNet's User guide (CompNet (2021)).[12]

3 Estimation

Markups. We apply the production approach of Hall (1986) and De Loecker & Warzynski (2012) to estimate markups. Assuming that intermediate inputs are flexible and that their prices are exogenous to firms, markups (μ_{it}) can be estimated from the firm's first order condition on intermediate inputs (online Appendix B.1 provides the full derivation):

$$\mu_{it} \equiv \frac{P_{it}}{MC_{it}} = \theta_{it}^{M} \frac{P_{it}Q_{it}}{z_{it}M_{it}}. \tag{1}$$

θ_{it}^{M} is the intermediate input output elasticity. MC_{it}, P_{it}, and Q_{it} denote marginal costs, prices, and quantities, respectively. $z_{it}M_{it}$ are intermediate input expenditures.

Markdowns. We follow the literature building upon Dobbelaere & Mairesse (2013) and consider that labor markets can feature firm-side (monopsony) and worker-side (rent-sharing) labor market power (e.g., Caselli et al. (2021), Yeh et al. (2022), Mertens (2022)). As shown in online Appendix B.2), combining the first order condition for labor with equation (1) yields an expression for labor markdowns:

[12] Recently, the data has been used in Berthou et al. (2020), Autor et al. (2020), and Bighelli et al. (2023).

$$\gamma_{it} \equiv \frac{MRP_{it}^L}{w_{it}} = \frac{\theta_{it}^L}{\theta_{it}^M} \frac{z_{it} M_{it}}{w_{it} L_{it}}. \quad (2)$$

θ_{it}^L is the output elasticity of labor. MRP_{it}^L, w_{it}, and L_{it} denote the marginal revenue product of labor, wages, and labor inputs, respectively.

Output elasticities. To estimate markups and markdowns, we need to recover firms' output elasticities by estimating firms' production functions.

For the German micro-data, we estimate a translog production function using a control function approach and account for firms' input *and* output price variation following De Loecker et al. (2016). From that, we obtain output elasticities that are not subject to the price bias. The precise method is explained in online Appendix C.[13]

The CompNet data directly contains markups derived from industry-specific Cobb-Douglas production functions. As we study the association between markups and firm size *within industries*, any biases in output elasticities will not affect our results. This is because the Cobb-Douglas production function defines constant *industry-specific* output elasticities which are absorbed by industry fixed effects. Hence, price and simultaneity biases are no concern for our results based on the CompNet data. Reassuringly, results are fully consistent with those obtained from the German data using a translog production function and firm-level prices.

[13] We follow the literature and rely on a translog production function. Our results are robust to various other specifications (i.e., different functional forms) and estimation approaches (OLS, Cobb-Douglas cost-shares, different input timing assumptions, time-varying production function coefficients).

4 Results

4.1 German manufacturing sector

We first present results for the German manufacturing sector as this database allows us to estimate market power measures based on a richer specification.

We estimate markups and markdowns for 242,303 firms. Average markups (markdowns) equal 1.10 (1.00) with a standard deviation of 0.04 (0.26).[14] Online Appendix Table C.1 provides more summary statistics for the German data.

Figure 1 shows binned scatter plots that project logged markups on logged firm size and absorb year and 4-digit industry fixed effects.[15] We find a strong negative association between firms' markups and size (Panel A), which turns positive after conditioning on markdowns (Panel B). This results from a negative correlation between firms' product and labor market power (Panel C). As suggested by these correlations, labor market power grows in firm size (Panel D).

[14] For the average firm, firm-side and worker-side market power offset each other. However, the average may not represent the aggregate as larger firms, which employ relatively more workers, have much higher markdowns.

[15] We focus on log-log relationships to minimize the effect of measurement error in the markup estimation. As markups are bounded by zero and binned scatter plots average markups by quantiles of sales, measurement errors may artificially increase average markups. If measurement noise is larger for small firms, this could artificially generate the negative relationship with firm size. The log-transformation prevents this.

MARKUPS AND FIRM SIZE, GERMAN MANUFACTURING SECTOR

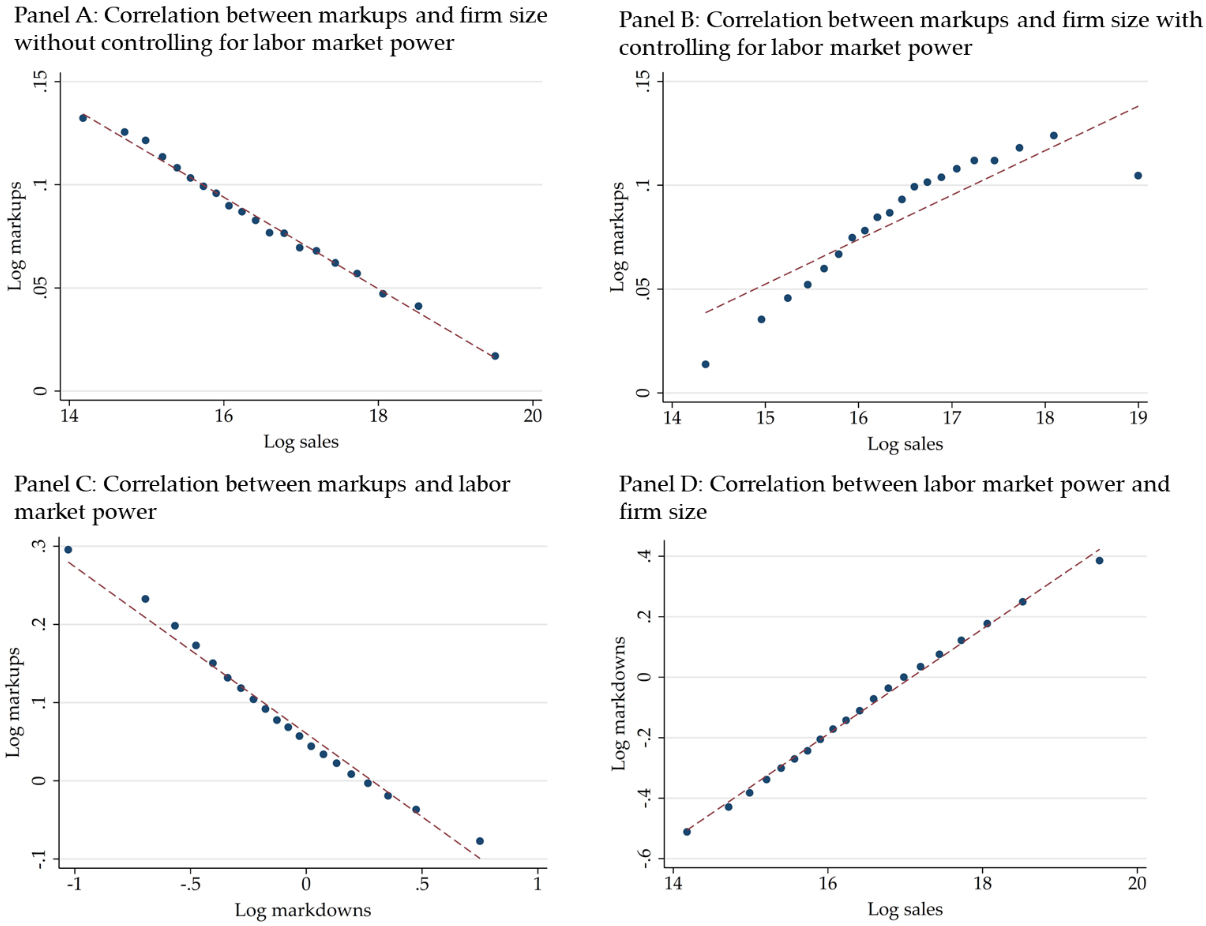


FIGURE 1 – Binned scatter plots from firm-level regressions. Panel A (B) shows results from projecting markups on firm size without (with) controlling for firms' markdowns. Panel C shows results from regressing markups on markdowns. Panel D shows results from regressing markdowns on firm size. All regressions control for industry and year fixed effects. German manufacturing sector data. 1995-2016. 242,303 firm-year observations.

Table 2 presents associated regression results from projecting markups on firm size while controlling for industry and year fixed effects. The results are in line with Figure 1 (columns 1-2) and hold when defining firm size in terms of employment (columns 3-4). Columns 5-8 reduce the sample to single-product firms and control for 10-digit product-fixed effects using data on firms' manufactured products. This controls for differences in firms' output that cannot be captured by industry fixed effects. Even from this restrictive specification comparing only single-product firms manufacturing the same product, we document a negative association between firms' markups and size that only turns positive after conditioning on markdowns.[16]

TABLE 2

MARKUPS AND FIRM SIZE								
	Log Markups							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log sales	-0.022***	0.021***			-0.020***	0.032***		
	(0.001)	(0.001)			(0.001)	(0.001)		
Log employment			-0.024***	0.022***			-0.022***	0.035***
			(0.001)	(0.001)			(0.002)	(0.001)
Log markdowns		-0.250***		-0.241***		-0.260***		-0.251***
		(0.003)		(0.002)		(0.004)		(0.004)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Product FE	No	No	No	No	Yes	Yes	Yes	Yes
Single product firms	No	No	No	No	Yes	Yes	Yes	Yes
Observations	242,303	242,303	242,303	242,303	82,942	82,942	82,942	82,942
R-squared	0.148	0.450	0.140	0.445	0.339	0.565	0.337	0.560
Num. firms	44,600	44,600	44,600	44,600	17,855	17,855	17,855	17,855

Notes: Table 2 reports results from projecting firm markups on firm size (sales). Columns 1-4 show results for the full sample. Columns 5-8 show results for the single-product firm sample. German manufacturing sector data. 1995-2016. Standard errors are reported in parentheses and clustered at the firm level. Significance: *10 percent, **5 percent, ***1 percent.

4.2 European evidence

To study how markups vary with the firms' size in Europe, we use the CompNet data's "joint distributions". These joint distributions report median markups, sales, and markdowns for each quintile of the firm sales distribution within each two-digit industry and year. Using these joint distributions, we regress markups on firm size at the industry-year-size-quintile level:

(3) $$\bar{\mu}_{kjt} = log(\overline{P_{\iota t}Q_{\iota t}})_{kjt} + \vartheta_j + \vartheta_t + \varepsilon_{kjt}.$$

[16] Online Appendix D.2.1 reproduces results using market shares as a size measure. Results are robust.

$\bar{\mu}_{kjt}$ and $log(\overline{P_{\iota t}Q_{\iota t}})_{kjt}$ are the logs of, respectively, median markups and median sales in quintile k of the sales distribution in two-digit industry j and year t. ϑ_j and ϑ_t capture industry and year fixed effects. We estimate this regression separately by country.

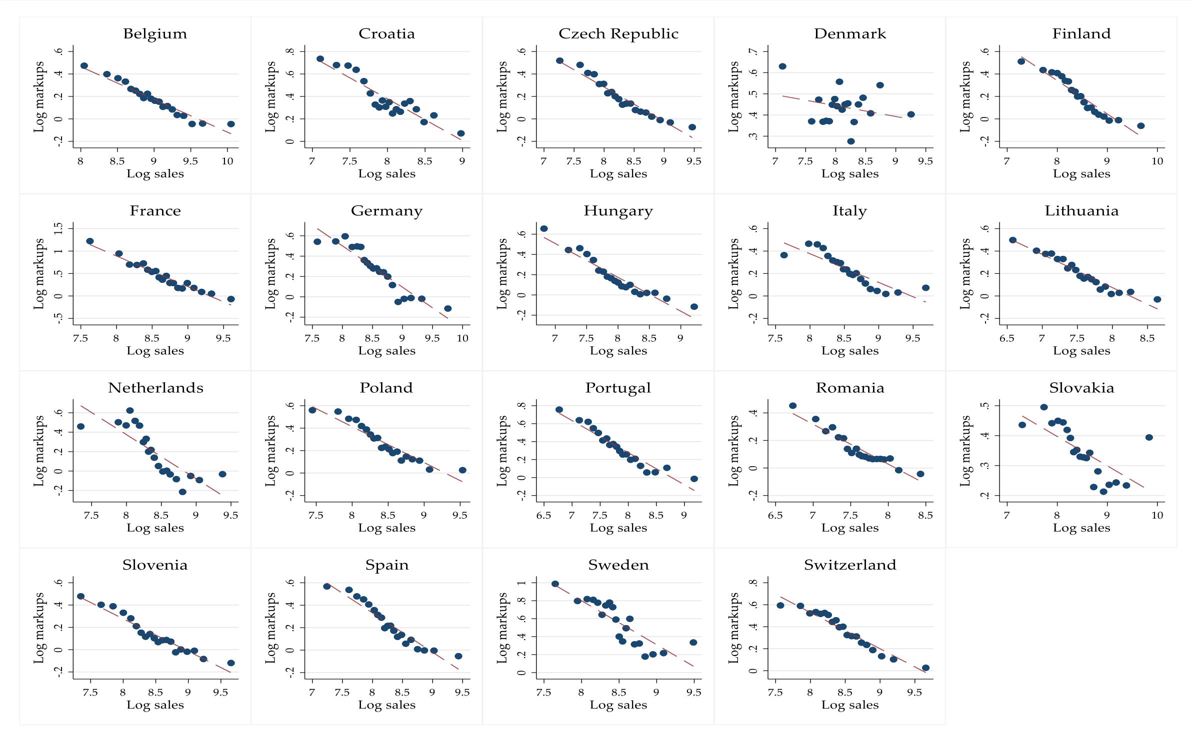
Figure 2 shows binned scatter plots from running the regression described in equation (3). Panel A shows a consistent unconditional negative association between markups and firm size for every country. Panel B reports the same plots after controlling for markdowns. Consistent with the results from the German data, all correlations between markups and firm size turn positive after conditioning on markdowns. Hence, labor market power is key in shaping the markup-size correlation.

Finally, Figure 3 shows results from projecting markups on markdowns and markdowns on firm size. In line with the German micro-data, markdowns and markups are negatively associated, whereas markdowns and firm size are positively correlated.

In summary, our findings show that the negative association between markups and firm size is a robust feature of the data. Despite larger firms are typically expected to face a less elastic demand (Marshall's second law of demand), they charge lower markups. This has important implication for a wide range of economic topics which we discuss in section 6.2.

MARKUPS AND FIRM SIZE ACROSS EUROPE

Panel A: Markups and firm size



Panel B: Markups and firm size controlling for labor markdowns

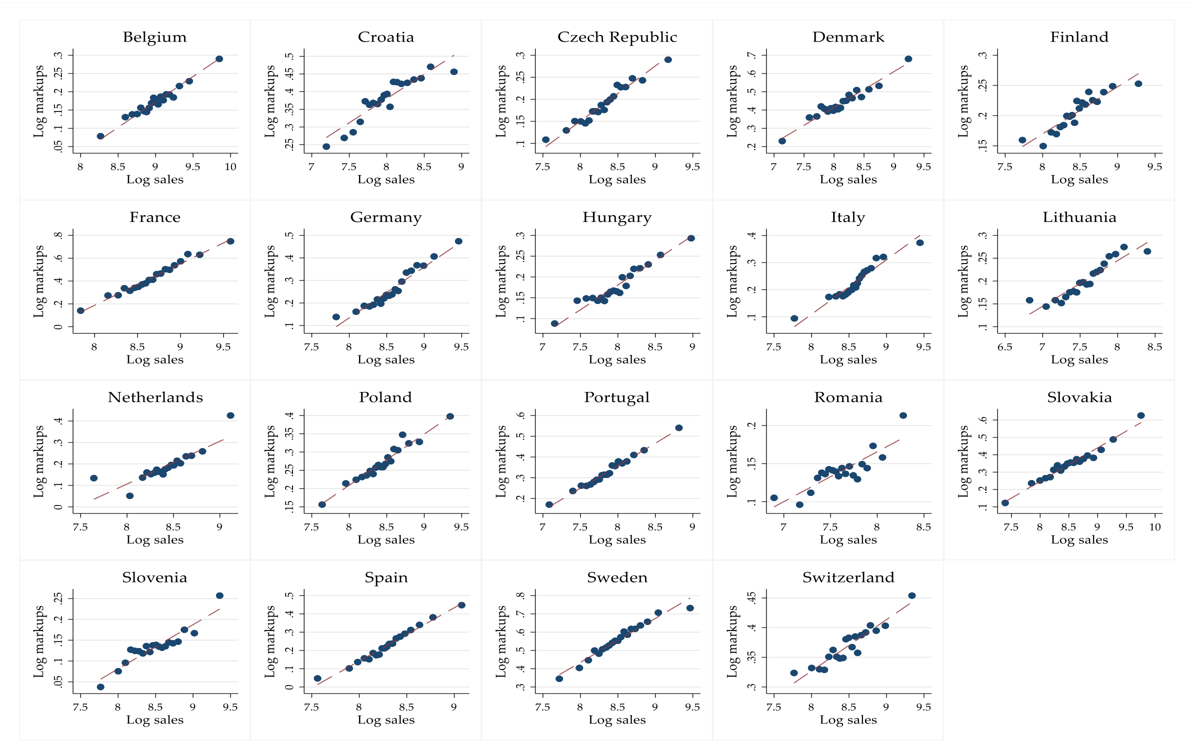
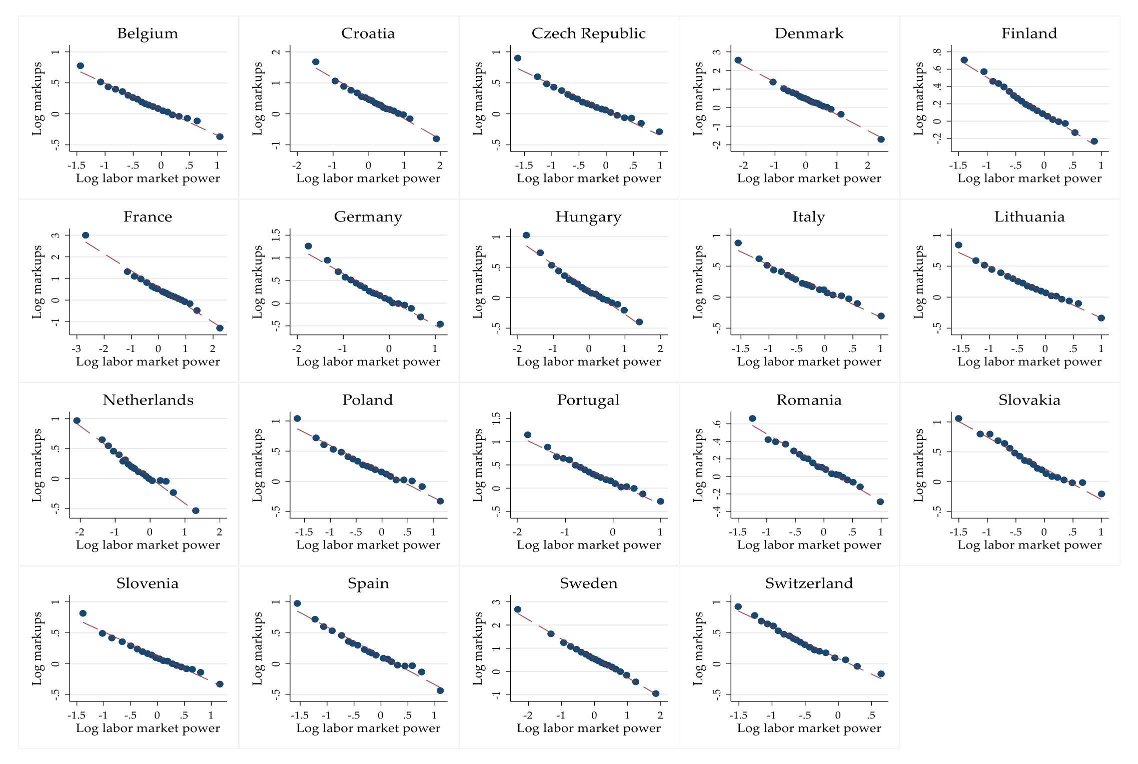


FIGURE 2 – Binned scatter plots from quintile-level regressions of median markups on median firm size along quintiles of the sales distributions within two-digit industries (all in logs). Panel A (B) reports results without (with) controlling for median log markdowns. All regressions control for year and industry fixed effects. CompNet data 1999-2018. Yearly and sectoral coverage varies by country as described in Table 1.

Panel A: Markdowns and markups



Panel B: Mardowns and firm size

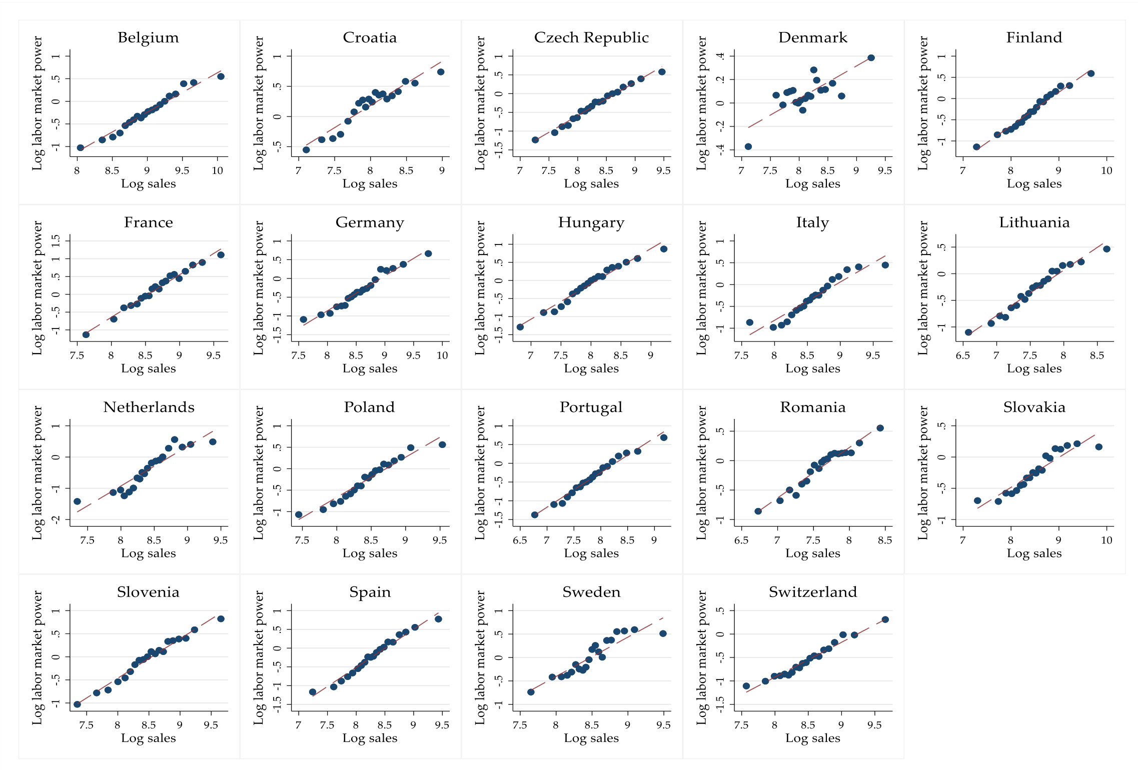


FIGURE 3 – Binned scatter plots from firm-level regressions of median markdowns on median markups (Panel A) and median markdowns on median firm size (Panel B) along quintiles of the sales distributions within two-digit industries (all in logs). All regressions control for year and industry fixed effects. CompNet data 1999-2018. Yearly and sectoral coverage varies by country as described in Table 1.

5 Robustness

5.1 Threats to identification

The production approach to markup estimation has recently received large attention in the literature. This subsection discusses the main criticism of this method and how it could affect our results.

Price bias. One main critique of the production approach arises from unobserved firm-level prices, which leads to biased estimates of output elasticities (Bond et al. (2021)). This concern does not apply to our study because our German data contains price data while our European analysis does not require production function estimation results. This is because, due to the Cobb-Douglas structure, output elasticities are constant across firms within industries. In this case, within-industry markup variation equals variation in input expenditure shares, leaving no room for biased output elasticities to affect our European results.

To further underline that the markup-size correlation in the German data is not an artefact of specificities of the complex production function estimation, online Appendix D.2.4 shows that assuming a Cobb-Douglas production function and using pure input shares reproduces the negative size-markup correlation.[17]

[17] Specifically, sales over intermediate expenditures are negatively correlated with firm size. We also show that labor shares are negatively correlated with firm size due to the positive correlation between markdowns and firm size .

Labor augmenting productivity. Recently, Raval (2023a) has argued that disregarding labor augmenting productivity could bias markups estimates if differences in firms' labor augmenting productivity are not captured in variation in output elasticities. Demirer (2020) showed that the bias in markups from labor augmenting productivity is particularly strong under Cobb-Douglas production functions while it is only small when using a translog production function. The latter is already reassuring as our results also hold when using a complex translog production function.

To further explore if labor augmenting productivity can explain our results, we follow Raval's (2023a, 2023b) approach and estimate production functions by industries and quintiles of firms with respect to their intermediate input expenditure over wage bill ratio, $\frac{z_{it}M_{it}}{w_{it}L_{it}}$, using the German micro-data. Raval (2023b) shows that variation in labor augmenting productivity is captured by the ratio $\frac{z_{it}M_{it}}{w_{it}L_{it}}$. He points out that estimating the production function by bins of this ratio accommodates differences in production function parameters driven by labor augmenting productivity.[18]

Online Appendix D.2.5 shows that following Raval's (2023a, 2023b) approach does not change our results. We still observe a smooth negative correlation between

---

[18] Raval (2023b) uses a cost share approach to estimate Cobb-Douglas production functions. We estimate our flexible translog production functions by firm groups, which, contrary to the cost share approach, allows for labor market power.

markups and firm size that only becomes positive after controlling for markdowns.[19] We conclude that differences in labor augmenting productivity levels between firms are unlikely to account for our findings.

Monopsony power in intermediates. Our approach to markup estimation requires a flexible input for which input prices are exogenous to firms. Following the literature, we rely on intermediate inputs. If firms held monopsony power in this market though, the right-hand side of equation (1) would be multiplied by the wedge $\gamma_{it}^{M} \equiv \frac{MRP_{it}^{M}}{z_{it}}$, where MRP_{it}^{M} is the marginal revenue product of intermediates. This wedge captures a firm's market power over its intermediate input suppliers. Our markups and markdowns (equations (1) and (2)) would then have, respectively, an upward and a downward bias growing in γ_{it}^{M}.

We are not concerned that this measurement error can explain our findings. Note that we are not interested in markup levels. Rather, we study the correlation between markups and firm size. To explain the negative markup-size correlation, intermediate input monopsony power would need to be higher in small than in large firms. Yet, the literature established the opposite (e.g., Morlacco (2020)).

Adjustment costs in intermediates. Another identification issue may arise if the flexible input chosen for the markup estimation is subject to adjustment costs (Bond et al. (2021)). However, this is unlikely to apply to our case, as intermediate inputs

[19] Table D.5 further shows that markup and markdown levels are similar to the baseline specification.

are typically not considered subject to adjustment costs in the literature (e.g., Hall (2004)).

Additionally, unobserved adjustments costs in intermediates may actually strengthen our results as they artificially create a *positive* association between firm size and markups (Gamber (2022)). This can be seen from the markup formula (1). For a given output elasticity, changes in sales that do not correspond to an adjustment in intermediate input expenditures create an artificial positive association between sales (i.e., size) and the markup.

Inputs that influence product demand. Finally, Bond et al. (2021) emphasize that markups are biased if the flexible input used in the markup estimation captures expenditures that influence product demand (e.g., marketing expenditures). To scrutinize this argument, online Appendix D.2.2 (Table D.3) runs regressions projecting markups on firm size for several firm groups. We split firms based on their industry-classification into firms mainly producing i) consumer goods, ii) intermediate goods, and iii) investment goods.[20] Arguably, marketing expenditures are much more relevant for consumer goods producers. Additionally, we split firms into exporter and non-exporter as exporting might involve additional overhead costs or marketing expenditures due to operating in multiple locations. Projecting markups on firm size separately across these firm groups does not yield any notable

[20] We classify industries following the Commission Regulation (EC) No 656/2007.

differences, suggesting that our results are not explained by unobserved product-demand-related intermediate input expenditures.

5.2 Comparison with other studies

Our findings seem to contradict several existing studies reporting a positive cross-sectional correlation between markups and firm size. Yet, a few studies also find that markups are lower in larger firms (Caselli et al. (2018), Diez et al. (2021)). Additionally, several studies document positive correlations between markups and firm size after conditioning on firm fixed effects, which relates *changes* in markups to *changes* in firm size (e.g., De Ridder et al. (2022)).[21] The latter is fundamentally different from the cross-sectional correlation highlighted in theoretical work and may absorb firm-specific factors related to labor market power.

How can we explain these findings in the literature? Interactions between product and labor market power and their impact on the markup-size correlation are determined by the underlying mode of competition and institutions. Variations in these factors across countries and industries might explain part of the differences between other studies and our findings.

However, our robust evidence for a negative association between markups and firm size across 19 European countries suggests that different approaches to

[21] Additionally, Burstein et al. (2020) report a positive correlation between markups and market shares in specifications either without industry fixed or with firm fixed effects. The latter, again, effectively compares changes, whereas the former does not account for heterogeneity between industries.

measuring markups might be more relevant. Recap that the markup is the wedge between the flexible input's output elasticity and that input's inverse expenditure share in sales (equation (1)). A key condition for estimating markups is that firms do not have market power in the flexible input's market. Hence, the methodology of Hall (1986) and De Loecker & Warzynski (2012) requires researchers to take a stance on which input is best suited for estimating markups.

Consider the case in which firms have labor market power, but intermediate input prices are exogenous. Deriving markups from firms' labor input decision yields a measure combining product and labor market power:

$$\mu_{it}^{L} = \theta_{it}^{L} \frac{P_{it}Q_{it}}{w_{it}L_{it}} = \mu_{it}\gamma_{it}, \tag{8}$$

where μ_{it}^{L} deviates from the true markup, μ_{it}. μ_{it}^{L} is the markup estimator used by De Loecker & Warzynski (2012), Autor et al. (2020), and several other studies. In the presence of labor market power, this expression reflects a meaningful measure of firms' overall market power on labor and output markets. Yet, results based on μ_{it}^{L} do not necessarily reflect a positive correlation between firm size and markups (μ_{it}) but could equally capture a positive correlation between labor markdowns (γ_{it}) and firm size. In fact, online Appendix D.2.3, Table D.3 shows that markups as computed in equation (8) *increase* with firm size, which results from the positive correlation between wage markdowns (γ_{it}) and firm size. Given widespread evidence on firm-and worker-side labor market power, relying on equation (8) to estimate markups might be problematic.[22]

Similarly, De Loecker et al. (2020) and De Loecker & Eeckhout (2020) combine labor and intermediates into one joint input when estimating markups. Assuming that intermediates are flexible and that intermediate input prices are exogenous to firms, their markup expression (μ_{it}^{DLEU}) is a weighted average of markups and markdowns: $\mu_{it}^{DLEU} = ((\theta_{it}^{M} + \theta_{it}^{L})/(\theta_{it}^{M}\gamma_{it} + \theta_{it}^{L}))\mu_{it}\gamma_{it}$ (see Mertens (2022)). Again, any positive association between μ_{it}^{DLEU} and firm size might reflect a positive association between labor markdowns and firm size (see online Appendix D.2.3).

6 Discussion

6.1 Mechanism

A striking result of our analysis is that controlling for markdowns restores the positive correlation between firm size and markups. This suggests that interactions between firms' product and labor market power, which are not captured by standard models, offer an appealing explanation for our findings. Such interactions could potentially drive firms to pursue different strategies to achieve profitability, depending on the prevailing market conditions and institutional arrangements. For instance, either by generating high markups and sharing rents with their workers, or

[22] See, for instance, Card et al. (2018), Mertens (2020, 2022), Brooks et al. (2021), Manning (2021).

by exploiting their workers and competing aggressively in their product markets through which firms can scale up their size.[23]

Deriving a full model featuring such market power interactions is beyond the scope of this study. Nonetheless, this section illustrates a simple rent-sharing setup that shows how worker power declining in firm size helps rationalizing our results.

As in standard bargaining models (e.g., Van Reenen (1996)), suppose that profit-maximizing firms bargain with risk-neutral workers over wages (w_{it}) and employment (L_{it}). Employees maximize utility:

$$U(w_{it},\, L_{it}) = w_{it}\, L_{it} + (\,\bar{L}_{it} - \, L_{it})\bar{w}_{it}. \tag{4}$$

$\bar{w}_{it} \leq w_{it}$ is the reservation wage. $\bar{L}_{it}$ is the competitive employment level. Firms produce output, Q_{it}, using the production function $Q_{it} = Q_{it}(L_{it}, K_{it}, M_{it}, e^{\omega_{it}})$. K_{it} and M_{it} denote capital and intermediates. ω_{it} is total factor productivity. We normalize the outside option of workers and firms to zero.[24] Formally, workers and firms solve the following Nash-bargaining problem:

$$\underset{Q_{it}}{Max}\ \phi_{it}(Q_{it}) log(w_{it}L_{it}) + \left[1 - \phi_{it}(Q_{it})\right] \log(P_{it}Q_{it} - C_{it}). \tag{5}$$

[23] Large firms have been observed to charge low prices while generating substantial profits and paying, compared to these profits, low wages in various real-life examples. Consider prices of large supermarkets like Walmart compared to Mom & Pop stores, or product and delivery service costs of Amazon compared to smaller retailers.

[24] This is not essential but simplifies the derivation. As Wong (2022) discusses, a zero-outside option for workers is consistent with the unresponsiveness of wages to large increases in unemployment insurance levels (Jäger et al. (2020)) and changes in the unemployment benefit duration (Le Barbanchon et al. (2019)).

C_{it} denotes the cost function. $\phi_{it} \in [0,1]$ denotes workers' bargaining power and is a function of firm size (Q_{it}).[25] This dependence of bargaining power on firm size is supported by empirical evidence but usually not considered in existing rent-sharing models.[26]

Taking the first order condition with respect to quantity yields:

$$\frac{\partial P_{it}}{\partial Q_{it}} Q_{it} + P_{it} - \frac{\partial C_{it}}{\partial Q_{it}} = \frac{\phi'(Q_{it})}{1-\phi(Q_{it})} log\left(\frac{\Pi_{it}}{w_{it}L_{it}}\right)\Pi_{it}, \tag{6}$$

where Π_{it} denote profits. Define $\tilde{\mu}_{it} \equiv \frac{1}{1+\frac{\partial P_{it} Q_{it}}{\partial Q_{it} P_{it}}}$ as the markup consistent with the standard markup rule. Importantly, this markup rule does not hold in this model.[27] To see this, rearrange equation (6):

$$\frac{1}{\tilde{\mu}_{it}} - \frac{1}{\mu_{it}} = \frac{\phi'(Q_{it})}{1-\phi(Q_{it})} log\left(\frac{\Pi_{it}}{w_{it}L_{it}}\right)\frac{\Pi_{it}}{P_{it}}, \tag{7}$$

where $\mu_{it} = \frac{P_{it}}{MC_{it}}$. In economic terms, equation (7) suggests that when worker power falls in firm size (i.e., $\phi'(Q_{it}) < 0$), the optimal markup (μ_{it}) will be lower than suggested by the elasticity of product demand. This gap between the two markup expressions increases with firm size and profitability. The rationale behind this is that firms with large rents may find it optimal to keep their markups low in order to

---

[25] Workers' bargaining may be lower in large firms because these firms can more easily resort to outsourcing or offshoring, as they can afford fixed costs associated to such actions. Alternatively, worker power may fall in size because coordination costs increase or because larger firms have higher labor market shares which limits the availability of alternative jobs.

[26] Using the same German micro-data, Mertens et al. (2022) show that larger firms have lower rent-sharing elasticities. Consistent with that, we document a positive association between markdowns and firm size.

[27] Combining the markup rule with the FOC for intermediate inputs yields that the usual markup estimator (equation (1)) is robust to this specification. Therefore, this model does not contradict our empirical strategy.

expand their market share, thereby enhancing their position in the labor market and decreasing their rent-sharing obligations. Depending on the shape of product demand and the size of $\phi'(Q_{it})$, this mechanism can become strong enough to cause markups to decline in firm size. The above analysis therefore highlights how interactions between firms' product and labor market power can provide a plausible explanation for the robust negative correlations between i) markups and firm size and ii) markups and markdowns.

6.2 Implications

In all 19 countries, markups are smaller in larger firms, whereas markups and markdowns are negatively correlated. What are the implications of our findings?

Misallocation and optimal policies. Markups create wedges in firms' first order conditions that distort the efficient production level and create misallocation (Hsieh & Klenow (2009)). A large literature attempts to quantify the economic losses from misallocation based on theories that model a positive markup-size correlation. If the correlation between markups and firm size is positive, markups cause large firms to underproduce. Consequently, size-dependent taxes (or antitrust policies) will reduce the aggregate markup but increase markup-induced misallocation in the economy (Edmond et al. (2023)). If markups are negatively correlated with firm size, as we document, size-dependent taxes can reduce misallocation from markup dispersion, reversing the policy's impact.

However, wage markdowns also distort the firm size distribution. Therefore, even if markups fall with firm size, large firms might underproduce if firms' input market power and size are positively correlated. The extent to which product and labor market power offset or strengthen each other is an empirical question. We document a negative correlation between both. This implies that size distortions from product and labor market power partially offset each other.

Hence, despite a negative markup-size correlation, overall wedges (i.e., $\mu_{it}^{L} = \mu_{it}\gamma_{it}$) can still grow with firm size if markdowns are sufficiently positively correlated with firm size (as we document). In that case, large firms still underproduce, as suggested by the literature, but for a different reason. Understanding how input and product market power relate to firm size (and productivity) and to each other is key for designing optimal policies because policies addressing both market power types differ. Whereas product competition policies predominantly affect markups, minimum wages or a strengthening of labor market institutions (unions, work councils, etc.) directly affect firms' labor market power. These policies thus create different effects on overall distortions and misallocation.

Concentration and factor shares. Rising market concentration has spurred large academic and public debates. On one hand, larger firms tend to possess superior management and technology, such that a reallocation of resources towards them can increase aggregate productivity (Bighelli et al., 2023). Conversely, such reallocation can induce undesirable effects if larger firms have higher markups. For instance, Autor et al. (2022) show that rising concentration resulted in a significant negative effect on the aggregate labor share. Although our findings reject the positive markup-size correlation, they do not necessarily relax the concern over rising concentration, because markdowns and the overall labor wedge grow in firm size. A reallocation of market shares toward larger firms can therefore still increase aggregate market power, which lowers factor shares.[28] However, according to our results, the channel would not be firms' product market power but imperfect competition in labor markets, where large firms exert more monopsony power and/or face less worker power.

International trade. The gains from trade in models with heterogenous markups change if markups decrease with firm size, because the extent to which trade can reduce markup-induced misallocation is defined by the joint distribution between firm size and markups (Edmond et al. (2015)). Intuitively, if the largest (most productive) producers do not have the largest markups, there is only small room for product market competition to reduce markups of large firms. Consequently the correlation between firm size and markups is key for determining optimal policies in the economy.

Demand estimation. Several studies derive markups by estimating demand elasticities. A subtle but crucial point from our discussion in Section 6.1 is that

[28] Combining equations (1) and (2) recovers the labor share $\left(\frac{W_{it}L_{it}}{P_{it}Q_{it}}\right)$ as a function of markups (μ_{it}) and markdowns (γ_{it}): $\frac{W_{it}L_{it}}{P_{it}Q_{it}} = \frac{\theta_{it}}{\mu_{it}\gamma_{it}}$.

interactions between rent-sharing processes and markups can lead firms to set markups not solely based on their demand elasticity. Therefore, studies that derive markups from estimating the demand elasticity should take into account potential interactions between labor and product market power among firms.

Pass-through and rent-sharing. The pass-through of shocks from firms to consumers and workers, depends on firms' relative market power in product and labor markets. For instance, the pass-through from cost-shocks to consumer prices is affected by firms' markups (De Loecker et al. (2016)). Similarly, shocks will be passed through to workers in form of lower/higher wages, depending on firms' labor market power. For instance, product market competition shocks reduce worker rents if there is rent-sharing. This is relevant in context of recent work emphasizing the potential negative effects of rising markups on wages and labor shares (e.g., De Loecker & Eeckhout (2020), Deb et al. (2022)).

Specifically, if firms share gains from product markups with their workers, labor market effects from rising markups are ambiguous and differ compared to situations without rent-sharing. In this case, higher markups may even increase wages and the negative labor market effects from rising markups on wages and labor shares discussed in the literature will be weakened or even reversed. Online Appendix B.2.3 proves this and shows that in a rent-sharing model firms' labor share *increases* in response to an increase in markups, if rent-sharing is sufficiently strong. Formally, a firm's labor share increases in response to an increase in the firm's markup if

$(\phi_{it}/(1-\phi_{it})) > (\theta_{it}^{L}/\sum_n \theta_{it}^{n})$, where ϕ_{it} denotes workers' bargaining power, θ_{it}^{L} is the output elasticity of labor, and $\sum_n \theta_{it}^{n}$ is the sum of output elasticities of other inputs that enter the profit function in the bargaining model.

7 Conclusion

This study documents novel empirical findings on firm-level markups, robust to common criticism (unobserved monopsony, price bias, non-neutral technology). We report a negative cross-sectional correlation between markups and firm size and reveal evidence of important interactions between product and labor market power. Our findings hold in a rich database of German manufacturing firms and in micro-aggregated data across a large set of European countries and sectors.

We discuss the implications of our findings and highlight that studying product and labor market power and their interactions in an integrated framework is key for future work as both market power types jointly characterize misallocation, factor shares, gains from trade, optimal policy, and the pass-through from firm shocks to consumers and workers.

References

Arkolakis, C., Costinot, A., Donaldson, D., & Rodríguez-Clare, A. (2019). The elusive pro-competitive effects of trade. *The Review of Economic Studies, 86*(1), 46-80.

Atkeson, A., & Burstein, A. (2008). Pricing-to-market, trade costs, and international relative prices. *American Economic Review, 98*(5), 1998-2031.

Autor, D., Dorn, D., Katz, L. F., Patterson, C., & Van Reenen, J. (2020). The fall of the labor share and the rise of superstar firms. *The Quarterly Journal of Economics, 135*(2), 645-709.

Bao, R., De Loecker, J., & Eeckhout, J. (2022). Are managers paid for market power?. *National Bureau of Economic Research (No. w29918).*

Berger, D. W., Herkenhoff, K. F., & Mongey, S. (2022a). Labor market power. *American Economic Review, 112(4), 1147-93.*

Berger, D. W., Herkenhoff, K. F., & Mongey, S. (2022b). Minimum wages, efficiency and welfare. *National Bureau of Economic Research (No. w29662).*

Bellone, F., Musso, P., Nesta, L., & Warzynski, F. (2016). International trade and firm-level markups when location and quality matter. *Journal of Economic Geography, 16*(1), 67-91.

Berthou, A., Chung, J. J. H., Manova, K., & Sandoz Dit Bragard, C. (2020). Trade, productivity and (mis) allocation. *CEP Discussion Paper No 1668.*

Bighelli, T., Di Mauro, F., Melitz, M. J., & Mertens, M. (2023). European firm concentration and aggregate productivity. *Journal of the European Economic Association, 21*(2), 455-483.

Boar, C., & Midrigan, V. (2019). Markups and inequality. *National Bureau of Economic Research (No. w25952).*

Bond, S., Hashemi, A., Kaplan, G., & Zoch, P. (2021). Some unpleasant markup arithmetic: Production function elasticities and their estimation from production data. *Journal of Monetary Economics, 121*, 1-14.

Burstein, A., Carvalho, V. M., & Grassi, B. (2020). Bottom-up markup fluctuations. *National Bureau of Economic Research (No. w27958).*

Brooks, W. J., Kaboski, J. P., Li, Y. A., & Qian, W. (2021). Exploitation of Labor? Classical Monopsony Power and Labor's Share. *Journal of Development Economics, 150,* article 102627.

Card, D., Cardoso, A. R., Heining, J., & Kline, P. (2018). Firms and labor market inequality: Evidence and some theory. *Journal of Labor Economics, 36*(S1), S13-S70.

Caselli, M., Schiavo, S., & Nesta, L. (2018). Markups and markdowns. *Economics Letters, 173,* 104-107.

Caselli, M., Nesta, L., & Schiavo, S. (2021). Imports and labour market imperfections: firm-level evidence from France. *European Economic Review, 131*, 103632.

CompNet (2021). User Guide for the 8th Vintage of the CompNet Dataset. *Accessible via: https://www.comp-net.org/data/8th-vintage/.*

Deb S., Eeckhout, J., Patel, A., & Warren, L. (2022). What drives Wage Stagnation: Monopsony or Monopoly?. *Mimeo.*

De Loecker, J. & Eeckhout, J. (2020). Global Market Power. Centre for Economic Policy Research. *Mimeo.*

De Loecker, J., & Eeckhout, J., Unger, G. (2020). The rise of market power and the macroeconomic implications. *The Quarterly Journal of Economics*, *135*(2), 561-644.

De Loecker, J., Goldberg, P. K., Khandelwal, A. K., & Pavcnik, N. (2016). Prices, markups, and trade reform. *Econometrica, 84*(2), 445-510.

De Loecker, J., & Warzynski, F. (2012). Markups and firm-level export status. *American Economic Review, 102*(6), 2437-71.

De Ridder, M., Grassi, B., & Morzenti, G. (2022). The hitchhiker's guide to markup estimation. *Mimeo.*

Dhingra, S., & Morrow, J. (2019). Monopolistic competition and optimum product diversity under firm heterogeneity. *Journal of Political Economy, 127*(1), 196-232.

Díez, F. J., Fan, J., & Villegas-Sánchez, C. (2021). Global declining competition?. *Journal of International Economics, 132*, 103492.

Dobbelaere, S., & Mairesse, J. (2013). Panel data estimates of the production function and product and labor market imperfections. *Journal of Applied Econometrics, 28*(1), 1-46.

Edmond, C., Midrigan, V., & Xu, D. Y. (2015). Competition, markups, and the gains from international trade. *American Economic Review, 105*(10), 3183-3221.

Edmond, C., Midrigan, V., & Xu, D. Y. (2023). How costly are markups? *Journal of Political Economy (forthcoming).*

Gamber, W. (2022). Entry and Employment Dynamics in the Presence of Market Power. *Mimeo*.

Hall, R. E. (1986). Market structure and macroeconomic fluctuations. *Brookings papers on economic activity, 1986*(2), 285-338**.**

Hall, R. E. (2004). Measuring factor adjustment costs. *The Quarterly Journal of Economics*, 119(3), 899-927.

Hashemi, A., Kirov, I., & Traina, J. (2022). The production approach to markup estimation often measures input distortions. *Economics Letters*, 217, 110673.

Hsieh, C. T., & Klenow, P. J. (2009). Misallocation and manufacturing TFP in China and India. *The Quarterly journal of economics, 124*(4), 1403-1448.

Hubmer, J., & Restrepo, P. (2022). Not a typical firm: The joint dynamics of firms, labor shares, and capital–labor substitution. *National Bureau of Economic Research (No. w28579).*

Jäger, S., Schoefer, B., Young, S., & Zweimüller, J. (2020). Wages and the Value of Nonemployment. *The Quarterly Journal of Economics, 135*(4), 1905-1963.

Jha, P., & Rodriguez-Lopez, A. (2021). Monopsonistic labor markets and international trade. *European Economic Review, 140*, 103939.

Le Barbanchon, T., Rathelot, R., & Roulet, A. (2019). Unemployment insurance and reservation wages: Evidence from administrative data. *Journal of Public Economics, 171*, 1-17.

Manning, A. (2021). Monopsony in labor markets: a review. ILR Review, 74(1), 3-26.

Macedoni, L. (2021). Monopsonistic competition, trade, and the profit share. *The Scandinavian Journal of Economics, 124*(2), 488-515.

Macedoni, L., & Weinberger, A. (2022). Quality heterogeneity and misallocation: The welfare benefits of raising your standards. *Journal of International Economics, 134*, 103544.

Marshall, A. (1936) Principles of Economics, 8th ed. (reprinted). London: Macmillan.

Mayer, T., Melitz, M. J., & Ottaviano, G. I. (2021). Product mix and firm productivity responses to trade competition. *Review of Economics and Statistics, 103*(5), 874-891.

Melitz, M. J., & Ottaviano, G. I. (2008). Market size, trade, and productivity. *The Review of Economic Studies, 75*(1), 295-316.

Mertens, M. (2020). Labor market power and the distorting effects of international trade. *International Journal of Industrial Organization, 68*, article 102562.

Mertens, M. (2022). Micro-mechanisms behind declining labor shares: Rising market power and changing modes of production. *International Journal of Industrial Organization, 81*, 102808.

Mertens, M., Müller, S., & Neuschäffer, G. (2022). Identifying rent-sharing using firms' energy input mix. *IWH Discussion Papers (No. 19/2022).*

Morlacco, M. (2020). Market power in input markets: Theory and evidence from french manufacturing. *Mimeo.*

Parenti, M. (2018). Large and small firms in a global market: David vs. Goliath. *Journal of International Economics, 110,* 103-118.

Peters, M. (2020). Heterogeneous markups, growth, and endogenous misallocation. *Econometrica, 88*(5), 2037-2073.

Raval, D. (2023a). Testing the production approach to markup estimation. *Review of Economic Studies*, forthcoming.

Raval, D. (2023b). Testing the production approach to markup estimation. *Economic Letters*, forthcoming.

Van Reenen, J. (1996). The creation and capture of rents: wages and innovation in a panel of UK companies. *The Quarterly Journal of Economics, 111*(1), 195-226.

Wong, H. C. (2023). Understanding high-wage firms. *Mimeo*

Yeh, C., Macaluso, C., & Hershbein (2022). Monopsony in the U.S. labor market. *American Economic Review, 112*(7), 2099-2138.

Zhelobodko, E., Kokovin, S., Parenti, M., & Thisse, J. F. (2012). Monopolistic competition: Beyond the constant elasticity of substitution. *Econometrica, 80*(6), 2765-2784.

Online Appendix – not for print

Appendix A: Details on the Data

Appendix A.1: German manufacturing sector data

Data access

The data can be accessed at the "Research Data Centres" of the Federal Statistical Office of Germany and the Statistical Offices of the German Länder. Data request can be made at: https://www.forschungsdatenzentrum.de/en/request. The statistics we used are: "AFiD-Modul Produkte", "AFiD-Panel Industriebetriebe", and "AFiD-Panel Industrieunternehmen".

Variable definitions

The following list presents an overview on the variable definitions for all variables used in this article (includes online Appendix).

- L_{it}: Labor in headcounts (end of September value).
- w_{it}: Firm wage (firm average), defined as gross salary + "other social expenses" (latter includes expenditures for company outings, advanced training, and similar costs) divided by the number of employees.
- K_{it}: Capital derived by a perpetual inventory method as described in Mertens (2020, 2022a), where investment captures firms' total investment in buildings, equipment, machines, and other investment goods. Nominal values are deflated by a two-digit industry-level deflator supplied by the statistical office of Germany.
- M_{it}: Deflated total intermediate input expenditures, defined as expenditures for raw materials, energy, intermediate services, goods for resale, renting, temporary agency workers, repairs, and contracted work conducted by other firms. Nominal values are deflated by a 2-digit industry-level deflator supplied by the statistical office of Germany.

- $z_{it}M_{it}$: Nominal values of total intermediate input expenditures.
- $P_{it}Q_{it}$: Nominal output / nominal total revenue, defined as total gross output, including, among others, sales from own products, sales from intermediate goods, revenue from offered services, and revenue from commissions/brokerage.
- Q_{it}: Quasi-quantity measure of physical output, i.e., $P_{it}Q_{it}$ deflated by a firm-specific price index (denoted by π_{it}, see below).[29]
- p_{igt}: Price of a product g.
- $share_{igt}$: Revenue share of a product g in total firm revenue.
- ms_{it}: Weighted average of firms' product market shares in terms of revenues. The weights are the sales of each product in firms' total product market sales.
- G_{it}: Headquarter location of the firm. 90% of firms in our German data are single-plant firms.
- D_{it}: A four-digit industry indicator variable. The industry of each firm is defined as the industry in which the firm generates most of its sales.
- E_{it} $(or\ in\ logs, e_{it})$: Deflated expenditures for raw materials. Nominal values are deflated by a 2-digit industry-level deflator for intermediate inputs and which is supplied by the statistical office of Germany. E_{it} is part of M_{it}.
- Exp_{it}: Dummy-variable being one, if firms generate export market sales.
- $NumP_{it}$: The number of products a firm produces.

Data preparation

During our 22 years of data, the NACE classification of industry sectors (and thus firms into industries) changed twice. Because the estimation of markups relies on a time-consistent industry classification at the firm level to estimate production functions, we require a time-consistent industry

[29] We observe quantities for the individual products of firms. Within multi-product firms, one cannot aggregate product quantities in a meaningful way. The measurement unit for each product is, however, designated by the statistical office. Hence, within products, aggregation of quantities is possible.

classification. Recovering such a time-consistent industry classification from official concordance tables is, however, problematic as they contain many ambiguous sector reclassifications.

To address this issue, we follow Mertens (2022a) and use information on firms' product mix to classify firms into NACE rev 1.1 sectors based on their main production activities. For details, we refer to Mertens (2022a).

Appendix A.2: The CompNet data

Data access and further documentation

Researchers can request data access to the CompNet data via: https://www.iwh-halle.de/en/research/data-and-analysis/research-data-centre/compnet-database/request-form. Further documentation on the data, including a detailed list of the underlying data sources, can be found in CompNet's 8th vintage User guide: https://www.comp-net.org/data/8th-vintage/.

Appendix B: Deriving Markups and Markdowns

Appendix B.1: Markups

We derive markups following the production approach of Hall (1986) and De Loecker & Warzynski (2012). Firm i in period t minimizes a variable cost function $C_{it} = w_{it}L_{it} + z_{it}M_{it} + r_{it}K_{it}$, subject to a constraint on the minimum level of output, produced using a continuous and twice differentiable production function $Q_{it} = Q_{it}(L_{it}, K_{it}, M_{it}, e^{\omega_{it}})$. L_{it}, M_{it}, and K_{it} denote labor, intermediates, and capital inputs, respectively, while w_{it}, z_{it}, and r_{it} are the associated unit input costs. ω_{it} denotes total factor productivity. Assuming that intermediate inputs are flexible and that their prices are exogenous to firms, the cost minimization problem yields the following FOC with respect to intermediate inputs:

$$z_{it} = \lambda_{it} \frac{\partial Q_{it}}{\partial M_{it}}, \tag{B.1}$$

where λ_{it} is the Lagrange multiplier and, in this setting, corresponds to the marginal cost. Our markup estimator (equation (1) in the main text) is obtained by combining condition (B.1) with the definition of the markup, $\mu_{it} = \frac{P_{it}}{\lambda_{it}}$, and the output elasticity, $\theta_{it}^{X} = \frac{\partial Q_{it}}{\partial X_{it}} \frac{X_{it}}{Q_{it}}$, where $X = \{L, M, K\}$:

$$\mu_{it} = \theta_{it}^{M} \frac{P_{it} Q_{it}}{z_{it} M_{it}}. \tag{B.2}$$

Appendix B.2: Markdowns

We follow recent work extending the production approach to derive an expression for markdowns. Some studies focus on monopsony power (e.g., Yeh et al. (2022)), whereas other work additionally allows for rent-sharing and worker bargaining power (e.g., Dobbelaere & Mairesse (2013), Mertens (2022a)). We first present a monopsony model in Appendix B.2.1 and subsequently discuss a model with rent-sharing in Appendix B.2.2. Both models yield the same markdown estimator.

Appendix B.2.1: Monopsony model

In standard monopsony models, labor is chosen in a static profit maximization problem without strategic interactions. Wages may vary with employment, as the firm-specific labor supply can be upward-sloping:

$$Max_{L_{it}}\, P_{it} Q_{it} - w_{it} L_{it} - z_{it} M_{it} - r_{it} K_{it}. \tag{B.3}$$

Rearranging the optimality condition, $MRP_{it}^{L} = \frac{\partial w_{it}}{\partial L_{it}} L_{it} + w_{it}$, one can express the markdown ($\gamma_{it} = \frac{MRP_{it}^{L}}{w_{it}}$) in terms of the slope of labor supply.

$$\gamma_{it} = 1 + \frac{\partial w_{it}}{\partial L_{it}} \frac{L_{it}}{w_{it}} \tag{B.4}$$

Firm’s optimal behavior is still consistent with the cost minimization problem in Appendix B.1. However, the left-hand side of the FOC with respect to labor does not perfectly mirror equation (B.1), because, unlike the price of intermediate inputs, wages are not exogenous to the firm’s decision:

(B.5) $$\frac{\partial w_{it}}{\partial L_{it}} L_{it} + w_{it} = \lambda_{it} \frac{\partial Q_{it}}{\partial L_{it}}.$$

Our markdown estimator (equation (2) in the main text) is obtained by first combining equations (B.4) and (B.5) with the definition of the output elasticity and then substituting in the markup estimator from equation (B.2).[30] Formally:

(B.6) $$\gamma_{it} = 1 + \frac{\partial w_{it}}{\partial L_{it}} \frac{L_{it}}{w_{it}} = \frac{\theta_{it}^{L}}{\theta_{it}^{M}} \frac{z_{it} M_{it}}{w_{it} L_{it}}.$$

Appendix B.2.2: Bargaining model

We follow standard bargaining models (e.g., McDonald & Solow (1981), Van Reenen (1996)), and assume that profit-maximizing firms bargain with risk-neutral workers over wages (w_{it}) and employment (L_{it}). Employees maximize their utility function, given by:

(B.7) $$U(w_{it},\, L_{it}) = w_{it}\, L_{it} + (\, \bar{L}_{it} - \, L_{it})\overline{w}_{it}.$$

$\overline{w}_{it} \leq w_{it}$ is the reservation wage. $\bar{L}_{it}$ is the competitive employment level. Firms produce output using the production function $Q_{it} = Q_{it}(L_{it}, K_{it}, M_{it}, e^{\omega_{it}})$. In the event of a breakdown of negotiations, workers receive the reservation wage, whereas the firm's outside option is to not produce at all. Formally, workers and firms solve the following Nash-bargaining problem:

(B.8) $$\max_{w_{it},\, L_{it},\, M_{it}, K_{it}} [\phi_{it} \log(\, L_{it}(w_{it} - \overline{w}_{it}) + (1-\phi_{it})\log(P_{it}Q_{it} - w_{it}L_{it} - z_{it}M_{it} - r_{it}K_{it})],$$

where $\phi_{it} \in [0,1]$ denotes workers' bargaining power. The first order condition with respect to L_{it} implies:

(B.9) $$w_{it}\left(1 - \frac{\phi_{it}}{1-\phi_{it}} \frac{\Pi_{it}}{w_{it}L_{it}}\right) = MRP_{it}^{L},$$

where Π_{it} denotes profits. Hence, wages exceed the marginal revenue product of labor in this model. Taking the first order condition with respect to output quantity, one can show that firms set

[30] The markup estimator can also be derived by taking the FOC with respect to intermediates from (B.3).

markups consistent with the markup rule in this framework.[31] This ensures us that $MRP_{it}^{L} = \frac{P_{it}}{\mu_{it}}\frac{\partial Q_{it}}{\partial L_{it}}$. Combining the latter with the markup expression (B.2) and the definition of the markdown yields the same estimator as in equation (B.6) and equation (2) of the main text:

$$\text{(B.10)} \qquad \gamma_{it} = \left(1 - \frac{\phi_{it}}{1-\phi_{it}}\frac{\Pi_{it}}{w_{it}L_{it}}\right) = \frac{\theta_{it}^{L}}{\theta_{it}^{M}}\frac{z_{it}M_{it}}{w_{it}L_{it}}.$$

Markdowns in the bargaining model have the same estimator as in the monopsony model, but the interpretation differs. Under monopsony, γ_{it} reflects the extent to which the labor supply elasticity allows firms to drive wages below competitive levels. In the bargaining model, γ_{it} reflects the extent to which worker power can drive wages above competitive levels. Together, both models provide intuitive explanations for why researchers observe $\gamma_{it} > 1$ and $\gamma_{it} < 1$ in the data. In some studies, these two frictions are used together to jointly motivate firm- and worker-side labor market power (e.g., Dobbelaere & Mairesse (2013), Caselli et al. (2021), Mertens (2022a)). We follow this interpretation.[32]

Appendix B.2.3: Labor shares, markups, and rent-sharing

The bargaining model from Appendix B.2.2 implies that an increase in firm markups does not necessarily lower firm-level labor shares if rents are largely redistributed to workers. Note that the FOC for labor yields:

$$\text{(B.11)} \qquad LS_{it} = \frac{w_{it}L_{it}}{P_{it}Q_{it}} = \frac{\theta_{it}^{L}}{\mu_{it}\gamma_{it}},$$

Now, express equation (B.10) as

$$\gamma_{it} = 1 - \frac{\phi_{it}}{1-\phi_{it}}\left(\frac{P_{it}Q_{it}}{w_{it}L_{it}} - 1 - \frac{z_{it}M_{it}}{w_{it}L_{it}} - \frac{r_{it}K_{it}}{w_{it}L_{it}}\right)$$

[31] I.e., $\mu_{it} = \frac{1}{1+\frac{\partial P_{it}Q_{it}}{\partial Q_{it}P_{it}}}$.

[32] Note that the above bargaining model is a static framework. This follows the standard rent-sharing literature (see Card et al. (2018) for a review). Strictly speaking, and as highlighted in Mertens (2020, 2022) and Garin & Silverio (2022), rent-sharing requires the existence of firm-side adjustment frictions (e.g., an organized community of workers, sunk training costs). Otherwise, workers have no leverage for bargaining with firms over rents.

$$\gamma_{it} = 1 - \frac{\phi_{it}}{1-\phi_{it}}\left(\frac{\mu_{it}\gamma_{it}}{\theta_{it}^{L}} - 1 - \gamma_{it}\frac{\theta_{it}^{M}}{\theta_{it}^{L}} - \gamma_{it}\frac{\theta_{it}^{K}}{\theta_{it}^{L}}\right),$$

(B.12)
$$\gamma_{it} = \frac{1}{(1-\phi_{it})} - \frac{\phi_{it}}{(1-\phi_{it})}\gamma_{it}\left(\frac{\mu_{it} - \theta_{it}^{M} - \theta_{it}^{K}}{\theta_{it}^{L}}\right),$$

where we used the definition of the output elasticity, $\theta_{it}^{X} = \frac{\partial Q_{it}}{\partial X_{it}}\frac{X_{it}}{Q_{it}}$, with $X = \{L, M, K\}$ and the FOC for intermediates and capital, which define $MRP_{it}^{M} = z_{it}$ and $MRP_{it}^{K} = r_{it}$, respectively.

Inserting (B.12) into (B.11) and rearranging, yields:

(B.13)
$$LS_{it} = \frac{\theta_{it}^{L}}{\mu_{it}}\left(1 - \phi_{it} + \phi_{it}\left(\frac{\mu_{it} - \theta_{it}^{M} - \theta_{it}^{K}}{\theta_{it}^{L}}\right)\right) = \phi_{it} + \frac{\theta_{it}^{L} - \phi_{it}\theta_{it}^{L} - \phi_{it}\theta_{it}^{M} - \phi_{it}\theta_{it}^{K}}{\mu_{it}}.$$

The derivative $\frac{\partial LS_{it}}{\partial \mu_{it}}$ is given by:

$$\frac{\partial LS_{it}}{\partial \mu_{it}} = -\underbrace{\frac{\theta_{it}^{L}}{\mu_{it}^{2}}}_{<0} + \underbrace{\frac{\phi_{it}\theta_{it}^{L}}{\mu_{it}^{2}}}_{>0} + \underbrace{\frac{\phi_{it}\theta_{it}^{M}}{\mu_{it}^{2}}}_{>0} + \underbrace{\frac{\phi_{it}\theta_{it}^{K}}{\mu_{it}^{2}}}_{>0},$$

which is positive if:

$$\frac{\partial LS_{it}}{\partial \mu_{it}} > 0 \; if \, \phi_{it}\theta_{it}^{L} + \phi_{it}\theta_{it}^{M} + \phi_{it}\theta_{it}^{K} > \theta_{it}^{L}$$

(B.14)
$$\frac{\partial LS_{it}}{\partial \mu_{it}} > 0 \; if \, \frac{\phi_{it}}{(1-\phi_{it})} > \frac{\theta_{it}^{L}}{\theta_{it}^{K} + \theta_{it}^{M}}.$$

Hence, if the relative bargaining power of workers, $\frac{\phi_{it}}{(1-\phi_{it})}$, is sufficiently strong, firm-level labor shares grow in response to increases in markups. Note that the denominator of the right-hand side depends on the specifications of profits. If bargaining is modelled in terms of short-run profits (that exclude capital), equation (B.14) will be expressed in terms of the labor and intermediate input output elasticities: $\frac{\partial LS_{it}}{\partial \mu_{it}} > 0 \; if \; \frac{\phi_{it}}{(1-\phi_{it})} > \frac{\theta_{it}^{L}}{\theta_{it}^{M}}$.

Appendix C: Estimating Output Elasticities in the German firm data

The following approach is closely in line with Mertens (2020, 2022a) and follows Olley & Pakes (1996), Wooldridge (2009), and De Loecker et al. (2016).

Production model

The translog production model we apply writes:

$$q_{it} = \boldsymbol{\phi}_{it}'\boldsymbol{\beta} + \omega_{it} + \varepsilon_{it}. \quad \text{(C.1)}$$

Lower case letters denote logs. $\boldsymbol{\phi}_{it}'$ captures the production inputs, K_{it}, L_{it}, and M_{it}, and its interactions.[33] ε_{it} is an i.i.d. error term. ω_{it} denotes Hicks-neutral productivity and follows a Markov process. Whereas ω_{it} is unobserved to the econometrician, firms know ω_{it} before making input decisions for flexible inputs. We allow that firms' input decisions for intermediates depends on productivity shocks. Labor and capital do not respond to contemporary productivity shocks and are quasi-fixed inputs. The timing assumption on labor addresses that our employment variable refers to employment at the end of September, whereas all other variables pertain to the full calendar year. Moreover, it is consistent with Germany's inflexible labor market setting and the presence of worker-side labor market power (see Appendix B.2.2).[34] However, all our results hold when allowing for flexible labor. This is not surprising because it is well-documented that variation in markups and markdowns is mostly driven by input expenditure shares (De Loecker 2021).[35]

There are three issues preventing us from directly estimating the production function (C.1) with OLS. First, although we observe product quantities, we cannot aggregate quantities across the products of multi-product firms. Yet, we need to estimate a quantity-based production model to

---

[33] The production function is: $q_{it} = \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} + \beta_{ll} l_{it}^2 + \beta_{mm} m_{it}^2 + \beta_{kk} k_{it}^2 + \beta_{lk} l_{it} k_{it} + \beta_{lm} l_{it} m_{it} + \beta_{km} k_{it} m_{it} + \beta_{lkm} l_{it} k_{it} m_{it} + \omega_{it} + \varepsilon_{it}$, where $\frac{\partial q_{it}}{\partial l_{it}} = \beta_l + 2\beta_{ll} l_{it} + \beta_{lm} m_{it} + \beta_{lk} k_{it} + \beta_{lkm} k_{it} m_{it}$ is the output elasticity of labor.

[34] Also other studies rely on quasi-fixed labor (e.g., De Loecker et al. (2016)). The appropriate timing assumptions on inputs always depend on the underlying setting and institutions.

[35] See also Appendix D.2.4 for how input shares relate to firm size.

recover output elasticities. Relying on sector-specific output deflators does not solve this issue if output prices vary within industries. Second, we do not observe firm-specific input prices for capital and intermediate inputs. If input prices are correlated with input decisions and output levels, we face an endogeneity issue. Third, the facts that productivity is unobserved, and that firms' flexible input decisions depend on productivity shocks create another endogeneity problem.

Solving issue 1: Deriving a firm-specific price index for firms' output

As it is impossible to aggregate output quantities across the different products of a firm, we construct a firm-specific price index from observed output price information following Eslava et al. (2004). We use this price index to purged firm revenue (for single- and multi-product firms) from price variation by deflating firm revenues with this price index.[36] Specifically, we construct firm-specific Törnqvist price indices for each firm's composite revenue from its various products:

$$PI_{it} = \prod_{g=1}^{n} \left(\frac{p_{igt}}{p_{igt-1}} \right)^{\frac{1}{2}(share_{igt}+share_{igt-1})} PI_{it-1}. \qquad \text{(C.2)}$$

π_{it} denotes the price index, p_{igt} is the price of good g, and $share_{igt}$ is the share of this good in total product market sales of firm i in period t. Hence, the growth of the index value is the product of the individual products' price growths, each weighted with the average sales share of that product over the current and last year. We define the first year in the data as the base year, i.e. $PI_{t=1995} = 100$. For firms entering after 1995, we follow Eslava et al. (2004) in using an industry average of our firm price indices as a starting value. Similarly, we follow impute missing product price growth information in other cases with an average of product price changes within the same industry.[37]

After deflating firm revenue with this price index, we end up with a quasi-quantity measure of output, for which, with slightly abusing notation, we keep using q_{it}.

[36] See also Smeets & Warzynski (2013) for an application of this approach.
[37] For roughly 30% of all product observations in our data, firms do not have to report quantities as the statistical office views them as not being meaningful.

Solving issue 2: Controlling for unobserved input price variation

To control for unobserved input price variation across firms, we follow De Loecker, et al. (2016) and define a price-control function from firm-product-level output price information that we add to the production function (C.1):

$$q_{it} = \widetilde{\boldsymbol{\phi}}'_{it}\boldsymbol{\beta} + B_{it}\big((PI_{it}, ms_{it}, G_{it}, D_{it}) \times \boldsymbol{\phi}^{c}_{it}\big) \; + \; \omega_{it} + \varepsilon_{it}. \quad \text{(C.3)}$$

$B_{it}(.) = B_{it}\big((\pi_{it}, ms_{it}, G_{it}, D_{it}) \times \boldsymbol{\phi}^{c}_{it}\big)$ is the price control function consisting of the firm-specific output price index (PI_{it}), a weighted average of firms' product market shares in terms of revenues (ms_{it}), a headquarter location dummy (G_{it}) and a four-digit industry dummy (D_{it}). $\boldsymbol{\phi}^{c}_{it} = \{1; \widetilde{\boldsymbol{\phi}}_{it}\}$, where $\widetilde{\boldsymbol{\phi}}_{it}$ includes the same input terms as $\boldsymbol{\phi}_{it}$, either in monetary terms and deflated by an industry-level deflator (capital and intermediates) or already reported in quantities (i.e., labor). The tilde indicates that some variables in $\widetilde{\boldsymbol{\phi}}_{it}$ are not expressed in true quantities. The constant entering $\boldsymbol{\phi}^{c}_{it}$ highlights that elements of $B(.)$ enter the price control function linearly and interacted with $\widetilde{\boldsymbol{\phi}}_{it}$ (a consequence of the translog production function).

The idea behind the price-control function is that firms' output prices, product market shares, location, and industry affiliation are informative about firms' input prices. Particularly, we assume that product prices and market shares contain information about product quality and that producing high-quality products requires expensive high-quality inputs. As discussed in De Loecker et al. (2016), this motivates to add a control function containing output price and market share information to the right-hand side of the production function to control for unobserved input price variation emerging form input quality differences across firms. Additionally, we include location and industry dummies into $B(.)$ to absorb remaining differences in local and industry-specific input prices.

Conditional on elements in $B(.)$, we assume that there are no remaining input price differences across firms.[38] Although being restrictive, this assumption is more general than the ones employed in

[38] We thus assume that input prices of intermediates and capital do not depend on input quantities, as these inputs enter the production function as deflated input expenditures.

most other studies that estimate production functions without access to firm-specific price data and which implicitly assume that firms face identical input and output prices within industries.

A notable difference between the original approach of De Loecker et al. (2016) and the one we apply is that De Loecker et al. (2016) estimate product-level production functions, whereas we transfer their framework to the firm-level. To do so, we use firm-product-specific sales shares in firms' total product market sales to aggregate firm-product-level information to the firm-level. By doing so, we assume that i) such firm aggregates of product quality increase in firm aggregates of product prices and input quality, ii) firm-level input costs for inputs entering as deflated expenditures are increasing in firm-level input quality, and iii) product price elasticities are equal across the various products of a firm. These assumptions, or even stricter versions of them, are always implicitly invoked when estimating firm- instead of product-level production functions.

Finally, note that even if some of the above assumptions do not hold, including the price control function is still preferable to omitting it. This is because the price control function can still absorb some of the unobserved price variation and does not demand that input prices vary between firms with respect to all elements of $B_{it}(.)$. The estimation can regularly result in coefficients implying that there is no price variation at all. The attractiveness of a price control function lies in its agnostic view about existence and degree of input price variation.

Solving issue 3: Controlling for unobserved productivity

To address the dependence of firms' flexible input decision on unobserved productivity, we employ a control function approach similar to Olley & Pakes (1996). We base our control function on firms' consumption of energy and raw materials, denoted by e_{it}, and which are components of total intermediate inputs. Inverting the demand function for e_{it} yields an expression for productivity:

$$\omega_{it} \equiv g_{it}(.) = g_{it}(e_{it}, k_{it}, l_{it}, \mathbf{\Gamma}_{it}). \tag{C.4}$$

$\mathbf{\Gamma}_{it}$ captures state variables of the firm, that in addition to k_{it} and l_{it} affect firms demand for e_{it}. Ideally, $\mathbf{\Gamma}_{it}$ should include a broad set of variables affecting productivity and demand for e_{it}. We include dummy variables for export activities (EX_{it}), the log of the number of products a firm produces ($NumP_{it}$) and the average wage it pays (w_{it}) into $\mathbf{\Gamma}_{it}$. The latter absorbs unobserved quality and price differences that shift demand for e_{it} (assuming that input prices are correlated).

Recap that productivity follows a first order Markov process. We allow that firms can shift this Markov process, giving rise to the following law of motion for productivity: $\omega_{it} = h_{it}(\omega_{it-1}, \boldsymbol{T}_{it-1}) + \xi_{it} = h_{it}(.) + \xi_{it}$, where ξ_{it} denotes the innovation in productivity and $\boldsymbol{T}_{it} = (EX_{it}, NumP_{it})$ reflects that we allow for learning effects from export market participation and (dis)economies of scope through adding and dropping products to influence firm productivity.[39] Plugging (C.4) and the law of motion for productivity into (C.3) yields:

$$q_{it} = \widetilde{\boldsymbol{\phi}}'_{it}\boldsymbol{\beta} + B_{it}(.) + h_{it}(.) + \varepsilon_{it} + \xi_{it}, \tag{C.5}$$

which constitutes the basis of our estimation.

Identifying moments

We estimate equation (C.5) separately by two-digit NACE rev. 1.1 industries using a one-step estimator as in Wooldridge (2009).[40] This estimator uses lagged values of flexible inputs (i.e., intermediates) as instruments for their contemporary values to address the dependence of firms' flexible input decisions on realizations of ξ_{it}. Similarly, we use lagged values of terms including firms' market share and output price index as instruments for their contemporary values as we consider these to be flexible variables.[41] We define identifying moments jointly for ε_{it} and ξ_{it}:

$$E\big((\varepsilon_{it} + \xi_{it})\mathbf{Y}_{it}\big) = 0, \tag{C.6}$$

[39] $\boldsymbol{T}_{it}$ and $\mathbf{\Gamma}_{it}$ both include the export dummy and the number of products a firm produces. This is not a problem for our estimation, as we are not interested in identifying the coefficients from the control functions.

[40] We approximate $h_{it}(.)$ by a third order polynomial in all of its elements, except for the variables in $\mathbf{\Gamma}_{it}$. Those we add linearly. $B_{it}(.)$ is approximated by a flexible polynomial where we interact the output price index with elements in $\widetilde{\boldsymbol{\phi}}_{it}$ and add the vector of market shares, the output price index, as well as location and industry dummies linearly. Interacting further elements of $B_{it}(.)$ with $\widetilde{\boldsymbol{\phi}}_{it}$ would create too many parameters to be estimated. This implementation is similar to De Loecker et al. (2016).

[41] This also addresses simultaneity concerns with respect to the price information entering the right-hand side of our estimation.

where $\mathbf{Y}_{it}$ includes lagged interactions of intermediate inputs with labor and capital, contemporary interactions of labor and capital, contemporary location and industry dummies, the lagged output price index, lagged market shares, lagged elements of $h_{it}(.)$, and lagged interactions of the output price index with production inputs. Formally:

$$\mathbf{Y}'_{it} = (J_{it}(.),\ A_{it-1}(.),\ T_{it-1}(.),\ \Psi_{it-1}(.),\ \boldsymbol{\nu}_{it-1}), \tag{C.7}$$

where for convenience we defined:

$J_{it}(.) = (l_{it}, k_{it}, l_{it}^2, k_{it}^2,\ l_{it}k_{it}, G_{it}, D_{it}),$

$A_{it}(.) = (\ m_{it}, m_{it}^2, l_{it}m_{it}, k_{it}m_{it}, l_{it}k_{it}m_{it}, ms_{it}, \pi_{it}),$

$T_{it}(.) = \Big((l_{it}, k_{it}, l_{it}^2, k_{it}^2,\ l_{it}k_{it}, m_{it}, m_{it}^2, l_{it}m_{it}, k_{it}m_{it}, l_{it}k_{it}m_{it}) \times \pi_{it}\Big),$

$\Psi_{it}(.) = \sum_{n=0}^{3}\sum_{w=0}^{3-b}\sum_{h=0}^{3-n-b}\ l_{it}^n\, k_{it}^b e_{it}^h$, and

$\boldsymbol{\nu}_{it} = (Exp_{it}, NumP_{it}, w_{it}).$

w_{it} denotes the average wage a firm pays.[42] We derive output elasticities from the production function as $\frac{\partial q_{it}}{\partial x_{it}} = \theta_{it}^X$ for $x = \{l, k, m\}$ and $X = \{L, K, M\}$. Median (mean) output elasticities for labor, capital, and intermediates across all industries equal 0.30 (0.29), 0.11 (0.11), 0.64 (0.64), respectively.[43] We then use equations (1) and (2) from the main text to estimate markups and markdowns. Finally, we tested various other estimation approaches, allowing for different timing assumptions (e.g., flexible labor), using different estimation routines (cost-shares, OLS), and even estimating time-varying translog production models, all yielding qualitatively similar results (results are available on request).[44]

[42] The inclusion of output price information on the right-hand side of the production function also helps to address concerns about potential violations of the "scalar unobservability" assumption as discussed in Doraszelski & Jaumandreu (2020).
[43] We drop observations with negative output elasticities as they are inconsistent with the production model we assume. This amounts to 5,797 (2.34%) of observations.
[44] We also do not purge measurement error and unanticipated shocks from output when estimating markups as this did not changes our results (results with the error correction are available on request).

Appendix D: Additional results

Appendix D.1: Summary statistics (German data)

TABLE D.1

SUMMARY STATISTICS FOR SAMPLE FIRMS, GERMAN MANUFACTURING SECTOR DATA

Variable	Mean (1)	Sd (2)	P25 (3)	Median (4)	P75 (5)	Observations (6)
Markups	1.10	0.04	0.98	1.07	1.19	242,303
Labor markdowns	1.00	0.26	0.66	0.90	1.22	242,303
Number of employees	304.28	2,223.95	47	94	224	242,303
Number of products	3.60	6.73	1	2	4	242,303
Log labor productivity	10.55	0.77	10.12	10.61	11.06	221,816
Labor share (value-added over wages)	0.78	0.07	0.63	0.76	0.88	242,303
Deflated intermediate input expenditures per employee in thousands	96.96	654,000	44.10	73.05	122.07	242,303
Deflated capital per employee in thousands	95.97	923,000	38.01	68.54	119.88	242,303

Notes: Table D.1 reports sample summary statistics. Columns 1, 2, 3, 4, 5, and 6 respectively report the mean, standard deviation, 25th percentile, median, 75th percentile, and the number of observations used to produce summary statistics for the respective variable. German manufacturing sector micro-data. 1995-2016.

Appendix D.2: Additional results

Appendix D.2.1: Using sales market shares as size measure (German data)

MARKUPS AND FIRMS' MARKET SHARES, GERMAN MANUFACTURING SECTOR

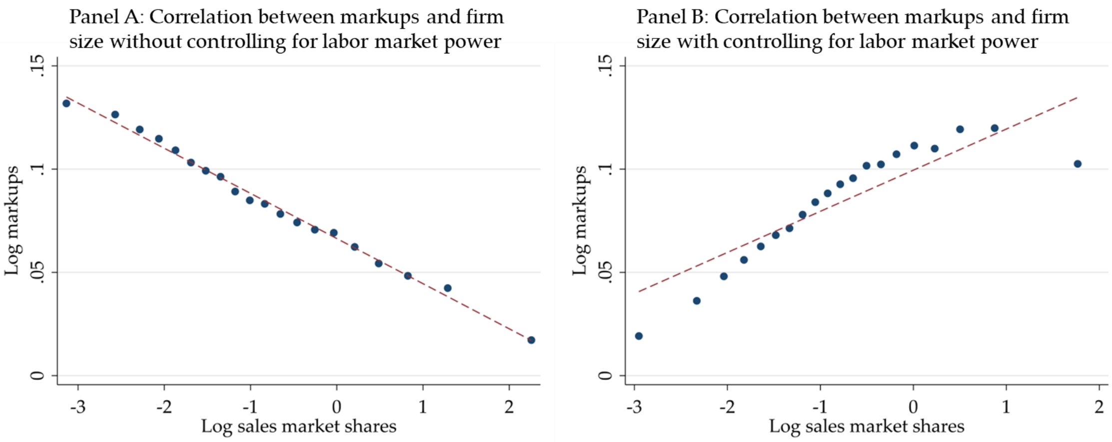


FIGURE D.1 – Binned scatter plots from firm-level regressions of log markups on log firm industry sales shares and log markdowns while controlling for year and four-digit industry fixed effects. Panel A (B) shows results from projecting markups on firm market shares without (with) controlling for firms' markdowns. German manufacturing sector data. 1995-2016. 242,303 firm-year observations.

TABLE D.2

MARKUPS AND MARKET SHARES				
	Log Markups			
	(1)	(2)	(3)	(4)
Log sales market share	-0.022*** (0.001)	0.020*** (0.001)	-0.014*** (0.001)	0.024*** (0.001)
Log markdowns		-0.247*** (0.003)		-0.246*** (0.004)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Product FE	No	No	Yes	Yes
Single product firms	No	No	Yes	Yes
Observations	242,303	242,303	82,942	82,942
R-squared	0.147	0.447	0.334	0.559
Num. firms	44,600	44,600	17,855	17,855

Notes: Table D.2 reports results from projecting firm markups on firms' industry sales shares. Columns 1-2 show results for the full sample. Columns 3-4 show results for the single product firm sample. German manufacturing sector data. 1995-2016. Standard errors are reported in parentheses and clustered at the firm level. Significance: *10 percent, **5 percent, ***1 percent.

Appendix D.2.2: Markup-size correlations for subgroups (German data)

Table D.3 reports the coefficients on firm size from the baseline regressions from Table 2, columns 1 and 2 for various firm groups. We always control for industry and year fixed effects.

TABLE D.3

MARKUPS AND FIRM SIZE FOR VARIOUS SUBGROUPS			
Subgroup of firms	Coefficient on firm size without controlling for markdowns (1)	Coefficient on firm size with controlling for markdowns (2)	Number of observations (3)
Consumer goods producers	-0.014*** (0.001)	0.015*** (0.001)	64,998
Intermediate goods producers	-0.025*** (0.001)	0.017*** (0.01)	102,324
Investment goods producers	-0.026*** (0.001)	0.037*** (0.01)	73,752
Exporter	-0.020*** (0.001)	0.023*** (0.001)	188,285
Non-Exporter	-0.027*** (0.001)	0.021*** (0.001)	54,014

Notes: Table D.3 reports regression coefficients on firm size from projecting firm markups on firms' size (sales) while controlling for year and industry fixed effects. Columns 1 and 2 report results without and with controlling for labor markdowns, respectively. Column 3 reports the number of observations entering the regressions. German manufacturing sector data. 1995-2016. Standard errors are reported in parentheses and clustered at the firm level. Significance: *10 percent, **5 percent, ***1 percent.

Appendix D.2.3: Other markup estimators used in the literature (German data)

FIRM SIZE AND MARKUPS BASED ON THE FOC OF LABOR

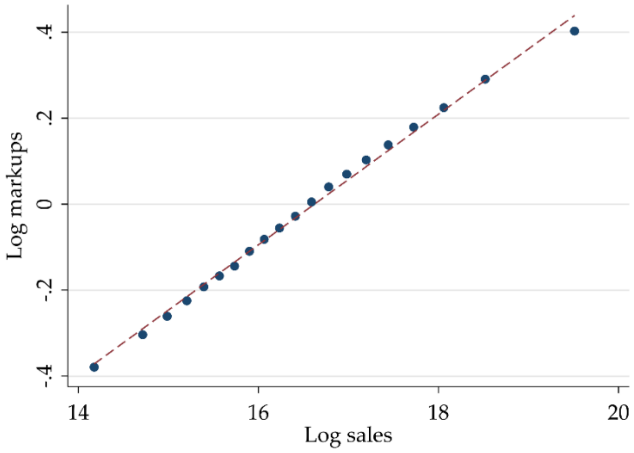


FIGURE D.2 – Binned scatter plots from firm-level regressions of logged labor input wedges (μ_{it}^{L}) on log firm size (sales) while controlling for year and four-digit industry fixed effects. Labor input wedges jointly reflect markups and wage markdowns ($\mu_{it}^{L} = \mu_{it}\gamma_{it} = \theta_{it}^{L}\frac{P_{it}Q_{it}}{w_{it}L_{it}}$). German manufacturing sector. 1995-2016. 242,303 firm-year observations.

FIRM SIZE AND MARKUPS BASED ON FIRMS' JOINT INPUT DECISION FOR INTERMEDIATES AND LABOR

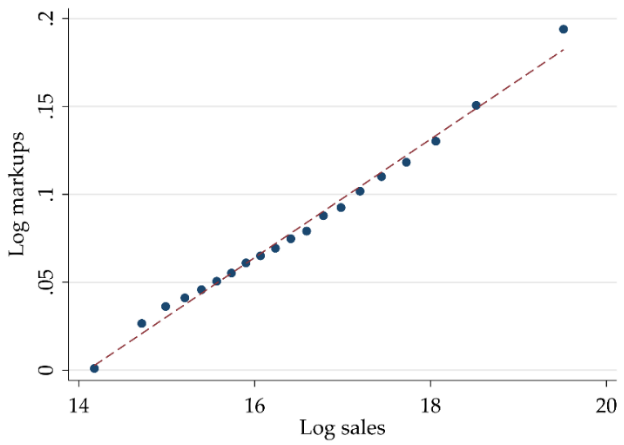


FIGURE D.3 – Binned scatter plots from firm-level regressions of the log of combined labor and intermediate input wedges (μ_{it}^{DLEU}) on log size (sales) while controlling for year and four-digit industry fixed effects. These input wedges jointly reflect markups and wage markdowns and are derived using the formula $\mu_{it}^{DLEU} = ((\theta_{it}^{M} + \theta_{it}^{L})/(\theta_{it}^{M}\gamma_{it} + \theta_{it}^{L}))\mu_{it}\gamma_{it}$. German manufacturing sector. 1995-2016. 242,303 firm-year observations.

In the main text, we discuss that several studies rely on biased estimates of markups if labor markets are imperfect. Here, we show that we can reproduce the positive correlation between firm size and these biased markup measures that has been documented in the literature. Figure D.2 relies on the markup equation (4) of the main text: $\mu_{it}^{L} = \mu_{it}\gamma_{it} = \theta_{it}^{L}\frac{P_{it}Q_{it}}{w_{it}L_{it}}$, which, among others, is used in Autor et al. (2020). Figure D.3 relies on $\mu_{it}^{DLEU} = ((\theta_{it}^{M} + \theta_{it}^{L})/(\theta_{it}^{M}\gamma_{it} + \theta_{it}^{L}))\mu_{it}\gamma_{it}$ as a markup expression which conceptionally replicates the markup expression in De Loecker et al. (2020).[45] Note that both markup expression combine markups with labor market power into one expression. Together with our main text results, we conclude that the positive correlation in Figures D.2 and D.3 is driven by a positive correlation between wage markdowns and firm size and does not reflect a positive correlation between markups and firm size.

Appendix D.2.4: Input shares and firm size (German data)

INPUT SHARES AND FIRM SIZE, GERMAN MANUFACTURING SECTOR

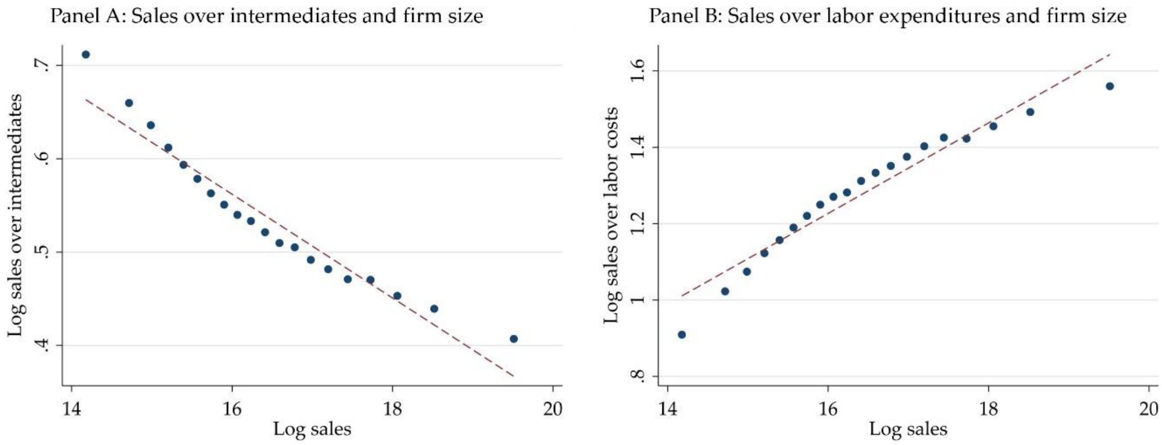


FIGURE D.4 – Binned scatter plots from firm-level regressions of log input shares on log firm size (sales) while controlling for year and four-digit industry fixed effects. Panel A (B) shows results from projecting sales over intermediate (labor) input expenditures on firm size. German manufacturing sector data. 1995-2016. 242,303 firm-year observations.

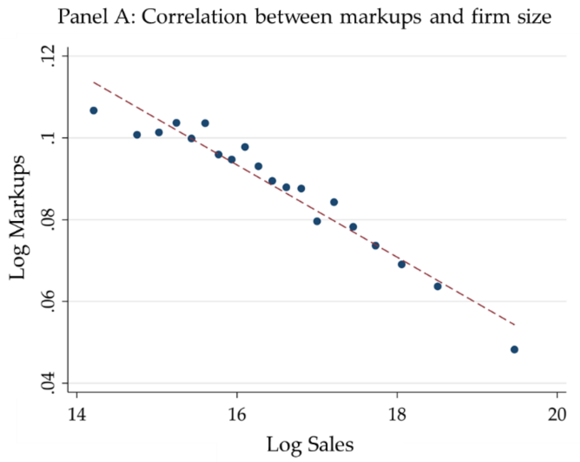
Figure D.4 projects the ratio of sales over intermediates and sales over labor costs on firm size. The former ratio captures a simple measure of markup-variation when output elasticities are constant across firms (see equation (1) of the main text). The second ratio reflects a simple measure of combined markup and wage markdown variation (see equation (4) of the main text). As expected, we find a negative correlation between firm size and sales over intermediates and a positive correlation between firm size and sales over labor costs (which is driven by a positive correlation between wage markdowns and firm size).

---

[45] We derive μ_{it}^{DLEU} from our production function estimates. De Loecker et al. (2020), instead estimate a production function combining labor and intermediates into one "variable" production factor. If this variable production factor contains only labor and intermediate inputs (or the respective input expenditures), if intermediates input prices are exogenous to firms, and if the underlying assumptions of combining labor and intermediates into one joint production factor (e.g., perfect substitutability between both inputs) are true, both approaches yield the same result.

Appendix D.2.5: Account for labor augmenting technology (German data)

MARKUPS AND FIRM SIZE WHEN ACCOUNTING FOR LABOR AUGMENTING TECHNOLOGY



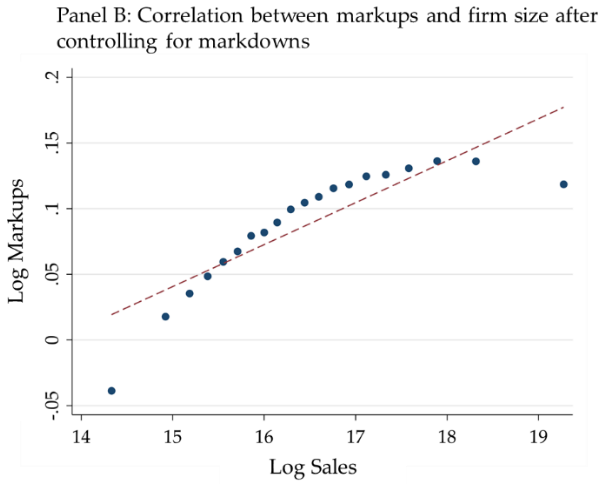


FIGURE D.5 – Binned scatter plots from firm-level regressions of log markups on log sales while controlling for year and four-digit industry fixed effects. Panel A (B) shows results without (with) controlling for firms' markdowns. German manufacturing sector data. 1995-2016. 224,821 firm-year observations.

TABLE D.4

MARKUPS AND MARKDOWNS, BASELINE VS. CONTROLLING FOR LABOR AUGMENTING TECHNOLOGY

	Baseline specification			Controlling for labor augmenting technology		
	mean (1)	median (2)	observations (3)	mean (4)	median (5)	observations (6)
Markups	1.10	1.07	242,303	1.12	1.11	224,821
Labor markdowns	1.00	0.90	242,303	1.06	0.83	224,821

Notes: Table D.4 reports sample means, medians, and observations counts for markups and markdowns using the baseline specification (columns 1-3) and the specification controlling for labor augmenting (columns 4-6).

References (online Appendix)

Autor, D., Dorn, D., Katz, L. F., Patterson, C., & Van Reenen, J. (2020). The fall of the labor share and the rise of superstar firms. *The Quarterly Journal of Economics, 135*(2), 645-709.

Card, D., Cardoso, A. R., Heining, J., & Kline, P. (2018). Firms and labor market inequality: Evidence and some theory. *Journal of Labor Economics, 36*(S1), S13-S70.

Caselli, M., Nesta, L., & Schiavo, S. (2021). Imports and labour market imperfections: firm-level evidence from France. *European Economic Review, 131*, 103632.

Crépon, B., Desplatz, R., & Mairesse, J. (2005). Price-cost margins and rent sharing: Evidence from a panel of French manufacturing firms. *Annales d'Economie et de Statistique*, 583-610.

De Loecker, J. (2021). Comment on (Un) pleasant... by Bond et al (2020). *Journal of Monetary Economics*, *121*, 15-18.

De Loecker, J., Goldberg, P. K., Khandelwal, A. K., & Pavcnik, N. (2016). Prices, markups, and trade reform. *Econometrica, 84*(2), 445-510.

De Loecker, J., & Eeckhout, J., Unger, G. (2020). The rise of market power and the macroeconomic implications. *The Quarterly Journal of Economics, 135*(2), 561-644.

Dobbelaere, S., & Mairesse, J. (2013). Panel data estimates of the production function and product and labor market imperfections. *Journal of Applied Econometrics*, *28*(1), 1-46.

Doraszelski, U., & Jaumandreu, J. (2020). The inconsistency of De Loecker and Warzynski's (2012) method to estimate markups and some robust alternatives. *Unpublished manuscript.*

Eslava, M., Haltiwanger, J., Kugler, A., & Kugler, M. (2004). The effects of structural reforms on productivity and profitability enhancing reallocation: evidence from Colombia. *Journal of development Economics*, *75*(2), 333-371.

Garin, A,, & Silvério, F. (2022). How Responsive are Wages to Demand within the Firm? Evidence from Idiosyncratic Export Demand Shocks. *Forthcoming in Review of Economic Studies.*

Hall, R. E. (1986). Market structure and macroeconomic fluctuations. *Brookings papers on economic activity*, *1986*(2), 285-338.

McDonald, I. M., & Solow, R. M. (1981). Wage Bargaining and Employment. The *American Economic Review, 71*(5), 896-908.

Mertens, M. (2020). Labor market power and the distorting effects of international trade. *International Journal of Industrial Organization*, *68*, article 102562.

Mertens, M. (2022a). Micro-Mechanisms behind Declining Labor Shares: Rising Market Power and Changing Modes of Production. *International Journal of Industrial Organization, 81*, 102808.

Mertens, M. (2022b). Labor Market Power, Superstar Firms, and Between-Firm Wage (In) Equality. *Mimeo.*

Mertens, M., Müller, S., & Neuschäffer, G. (2022). Identifying rent-sharing using firms' energy input mix. *IWH Discussion Papers (No. 19/2022).*

Olley, G. S., & Pakes, A. (1996). The Dynamics of Productivity in the Telecommunications Equipment. *Econometrica, 64*(6), 1263-1297.

Smeets, V., & Warzynski, F. (2013). Estimating productivity with multi-product firms, pricing heterogeneity and the role of international trade. *Journal of International Economics*, *90*(2), 237-244.

Van Reenen, J. (1996). The creation and capture of rents: wages and innovation in a panel of UK companies. *The Quarterly Journal of Economics*, *111*(1), 195-226.

Wooldridge, J. M. (2009). On estimating firm-level production functions using proxy variables to control for unobservables. *Economics letters, 104*(3), 112-114.

Halle Institute for Economic Research –
Member of the Leibniz Association

Kleine Maerkerstrasse 8
D-06108 Halle (Saale), Germany

Postal Adress: P.O. Box 11 03 61
D-06017 Halle (Saale), Germany

Tel +49 345 7753 60
Fax +49 345 7753 820

www.iwh-halle.de

ISSN 2194-2188

Leibniz
Association

The IWH is funded by the federal government and the German federal states.