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

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Abstract

Combining financial statements with firm-level product prices, we find that larger firms exhibit *lower* markups, although they are overcompensated by substantially higher wage markdowns. We explain our divergence from prior results by highlighting how labor market power affects markup estimates.

Keywords: *Market power*; *markups*; *markdowns*; *firm size*

JEL Codes: *L11; L13; L25; J42*

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1 Introduction

Recent evidence on the rise in product market concentration across advanced economies has drawn attention to the competitive behavior of large firms and its broader implications (De Loecker et al., 2020; Autor et al., 2020; Bighelli et al., 2022). A central aspect of this debate is the relationship between firm size and market power: do larger companies charge substantially higher markups than their smaller competitors?[1]

This paper reassesses this hypothesis, using a rich database from German administrative sources to measure markups with the "production approach" (Hall, 1986; De Loecker and Warzynski, 2012). Leveraging these comprehensive data, which include information on firm-level product prices, we estimate industry-specific translog production functions and recover estimates unaffected by the price bias, a known issue of markup estimation (Bond et al., 2021). Markups are derived from firms' optimal choice of intermediate inputs—instead of labor—to allow for the presence of labor market power. Following Dobbelaere & Mairesse (2013), we combine our estimated markups with the firms' optimal choice of labor to separately identify wage markdowns.[2]

Our results are striking: within product markets and industries, larger firms charge *lower* markups. We examine well-known identification threats to the production approach, including the role of labor-augmenting productivity and other common issues, and argue that none of these factors can rationalize the negative relationship between markups and firm size observed in the data.[3] Extending our analysis to a broader sample from the CompNet database, we confirm our results in a simplified setting for 19 countries.

Finally, we discuss potential reasons why previous studies adopting a similar approach found different results.[4] Our main insight is that failing to account for labor market power in markup estimation introduces a bias, resulting in a positive correlation between markups and firm size. Specifically, recovering markups from labor decisions leads to an estimator capturing both price markups and wage markdowns, and we show that the

[1]Theoretically, this relationship holds in the canonical Cournot model as well as recent contributions, such as Atkeson & Burstein (2008), Melitz & Ottaviano (2008), Edmond et al. (2015, 2023), Parenti (2018), Boar & Midrigan (2019), Burstein et al. (2020), Peters (2020), Hubmer & Restrepo (2022), Bao et al. (2022), and Macedoni & Weinberger (2022).

[2]Markdowns are defined as the marginal revenue product of labor over labor costs per worker. Following the literature, we interpret them as a measure of labor market power.

[3]For a critical assessment of the production approach to markup estimation see Bond et al. (2021), Hashemi et al. (2022), Raval (2023), and De Ridder et al. (2025).

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

positive correlation between this joint market power term and firm size results from markdowns rather than markups. While wage markdowns increase in size, markups fall, and because the former effect dominates, the indicator of joint market power is higher for large firms.

2 Estimation

Data. Our analysis uses firm-product-level panel data from the AFiD database, supplied by the Statistical Offices of Germany. The data cover German manufacturing firms with at least 20 employees (1995-2016), with information on firms' employment, investment, revenue, and, most importantly, product quantities and prices at a ten-digit product classification. Appendix A provides further details and summary statistics for the German data, together with a description of the CompNet database used for robustness.

Markups. Firm i in period t minimizes a variable cost function $C_{it} = w_{it}(L_{it})L_{it} + z_{it}M_{it} + r_{it}K_{it}$, subject to 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. w_{it}, z_{it}, and r_{it} are the associated unit input costs. ω_{it} denotes total factor productivity (in logs).

Assuming that intermediate inputs are flexible and that their prices are exogenous to firms, the cost minimization problem yields the following first-order condition:

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

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

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

Markdowns. In this Section, we derive the markdown in a standard monopsony model. Derivations within a rent-sharing setting, reported in the online Appendix B, yield the same markdown estimator.

Wage markdowns, γ_{it}, are defined as the ratio of the marginal revenue product of labor to the wage. In a static problem of profit maximization, this ratio departs from one when the firm observes an upward-sloping labor supply.

$$\gamma_{it} \equiv \frac{MRP_{it}^{L}}{w_{it}} = 1 + \frac{\partial w_{it}}{\partial L_{it}} \frac{L_{it}}{w_{it}} \tag{3}$$

Considering the cost minimization problem introduced to derive the markup, the first-order condition for labor does not perfectly mirror equation (1), as wages are not exogenous to the firm.

$$w_{it} \left(1 + \frac{\partial w_{it}}{\partial L_{it}} \frac{L_{it}}{w_{it}}\right) = \lambda_{it} \frac{\partial Q_{it}}{\partial L_{it}} \tag{4}$$

Our markdown estimator is obtained by combining equations (2), (3), and (4) with the definitions of markup and output elasticity.

$$\gamma_{it} = \frac{\theta_{it}^{L}}{\theta_{it}^{M}} \frac{z_{it} M_{it}}{w_{it} L_{it}} \tag{5}$$

Output elasticities. To recover markups and markdowns, we need estimates of the output elasticities of intermediate inputs and labor. We estimate industry-specific translog production functions, using a control function approach to deal with the simultaneity bias (Ackerberg et al., 2015) as well as the input price bias (De Loecker et al., 2016). To account for firm heterogeneity in output prices, we employ firm-specific product-level prices and deflate revenues with a firm-level price index (Eslava et al., 2004). We detail the full methodology in online Appendix C. Our results are robust to a variety of alternative specifications and estimations approaches.

3 Results

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).[5] Note that averages do not represent the aggregate. As shown below, larger firms, employing relatively more workers, have much higher markdowns.

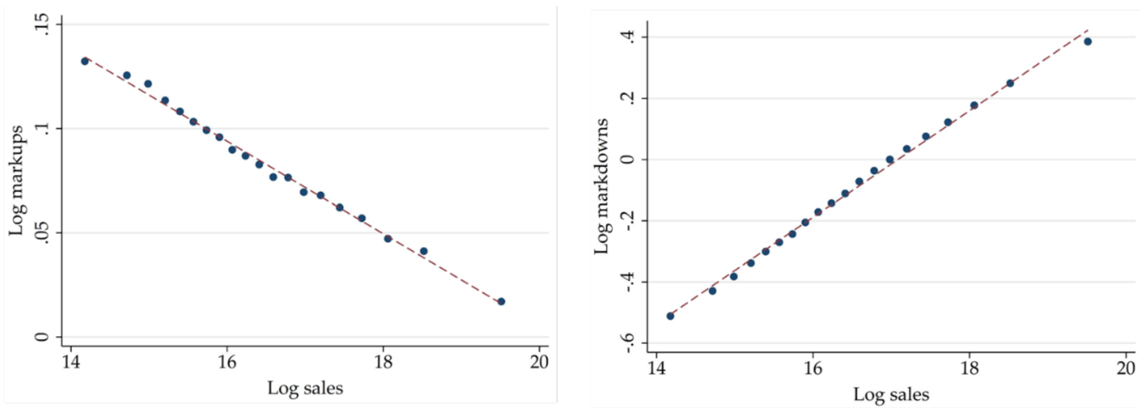
Figure 1 summarizes our key findings using binned scatter plots that project logged markups and markdowns on firm size (sales) after absorbing year and 4-digit industry

[5]As shown in Appendix B, markdown values below unity can be explained by rent-sharing.

fixed effects.[6] We observe a strong *negative* association between firms' markups and size (Panel A). Markdowns and firm size are strongly positively correlated (Panel B).

FIGURE 1. MARKET POWER AND FIRM SIZE

Panel A. Markups and firm size. Panel B. Markdowns and firm size



Note: Binned scatter plots with industry and year fixed effects. Panel A (B) shows results from projecting markups (markdowns) on sales. German manufacturing sector data. 1995-2016. 242,303 firm-year observations.

Table 1 further focuses on the negative association between markups and firm size, which is our main finding. Column 1 reports the regression coefficient underlying Panel A of Figure 1, which is highly statistically significant. Column 2 uses employees as an alternative size measure, which yields a similar result. Finally, Columns 3-4 reduce the sample to single-product firms and control for 10-digit product-fixed effects using data on firms' manufactured products.[7] This specification controls for differences in output characteristics that cannot be captured by industry fixed effects. Again, results are almost unchanged.

[6]Because markups are defined on a positive interval, measurement errors may increase the average estimates. Larger noise for small firms could artificially generate a negative relationship between markups and firm size in levels. The log-transformations prevent this issue.

[7]There are approximately 6,000 10-digit product categories. Examples are "Tin sheets and tapes, thicker than 0.2mm" or "Workwear: long trousers for men, cotton".

TABLE 1. REGRESSION RESULTS

	Log Markups			
	(1)	(2)	(3)	(4)
Log sales	-0.022***		-0.020***	
	(0.001)		(0.001)	
Log employment		-0.024***		-0.022***
		(0.001)		(0.002)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Product FE	No	No	Yes	Yes
Multi-product firms	Yes	Yes	No	No
Observations	242,303	242,303	82,942	82,942
Num. firms	44,600	44,600	17,855	17,855
R-squared	0.148	0.140	0.339	0.337

Note: Table 1 reports results from regressing markups on firm size (sales and employees). Columns 1-2: full sample. Columns 3-4: 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 Comparison to other studies

Several applications of the production approach to markup estimation rely on firm's optimal choice of labor, assuming perfectly competitive labor markets (Hall, 1986, De Loecker & Warzynski, 2012, Autor et al., 2020).[8] When labor market power is present, this approach recovers the product of price markups and wage markdowns, a joint measure of market power in both markets:

$$\mu_{it}^{L} = \theta_{it}^{L} \frac{P_{it} Q_{it}}{w_{it} L_{it}} = \mu_{it} \gamma_{it}. \tag{6}$$

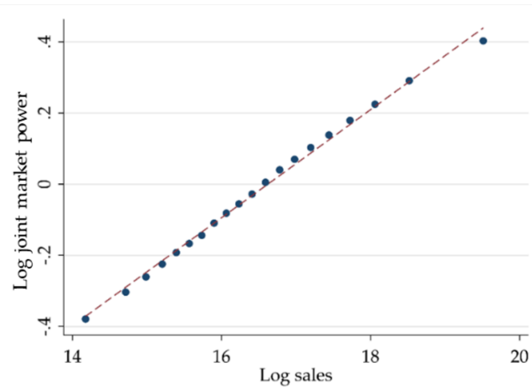
Using this joint measure, we indeed find a robust positive correlation with firm size (Figure 2). Our previous results (Figure 1) disentangle these two sources of market power, showing that the correlation observed in Figure 2 is entirely driven by wage markdowns.[9]

[8]Other studies derive markups from intermediate input decisions without focusing on their cross-sectional correlation with firm size.

[9]Similarly, De Loecker et al. (2020) combine labor and intermediates into a variable input bundle, which also yields a combined measure of firms' markups and markdowns.

Hence, in our data, larger firms possess higher market power not because of higher markups, but because due to their position in labor markets.

FIGURE 2. JOINT MARKET POWER AND FIRM SIZE



Note: Binned scatter plot projecting the joint measure of market power on sales, with industry and year fixed effects. The indicator of joint market power is defined in Equation (6). German manufacturing sector data. 1995-2016. 242,303 firm-year observations.

5 Robustness

Threats to identification. Recently, the production approach to markup estimation has received large attention. Two common critiques concern the price bias, which arises when markups are estimated with revenue data (Bond et al., 2021), and the estimation bias induced by cross-sectional heterogeneity in labor-augmenting productivity (Raval, 2023). As we have access to firm-level product prices, our estimation is unaffected by the former threat. We now discuss the role of labor-augmenting productivity and how it could affect our results. Additional robustness checks for other potential issues—monopsony power over suppliers, adjustment costs in intermediate inputs, and inputs affecting the product demand—are provided in the online Appendix D.3.

Imposing a production function with Hicks-neutral technology may bias markup estimates if cross-sectional differences in labor-augmenting productivity are not fully captured by variation in output elasticities.[10] To explore whether firm heterogeneity in non-neutral technology can explain our results, we accommodate differences in labor-augmenting productivity following Raval's (2023) suggestion: firms are split by quintiles

[10]Demirer (2025) shows that this bias is particularly strong under Cobb-Douglas production functions and smaller when using a translog specification, which is reassuring for us.

of the intermediate-to-labor expenditure ratio, and production functions are separately estimated for each group.[11] Using these estimates, we still observe a smooth negative (positive) correlation between markups (markdowns) and firm size.[12]

Evidence from other samples. To provide further evidence, we extend our analysis to a larger sample covering most sectors from 19 European countries, under a simplifying assumption. We exploit that, within the framework of Hall (1986), a Cobb-Douglas production function implies that the observed firm-level cost shares are the only source of cross-sectional variation in markups between firms from the same industry.[13] Hence, firm heterogeneity in product market power can be assessed without estimating production functions, making the results immune to the price bias and other issues related to production function estimation. Using this simple yet widely applied specification, we test the markup-size relationship using CompNet data and confirm the key results for each of the 19 countries examined.[14] A detailed description of the CompNet data collection and aggregation is reported in Appendix A.2, while our empirical analysis and results are illustrated in Appendix D.1.

6 Conclusion

This study provides new insights on firm heterogeneity in competitive behavior across product and labor markets, uncovering a somewhat unexpected pattern: within narrow industries, markups fall in firm size. Yet, larger firms have greater wage markdowns, which overcompensates the negative markup-size correlation. Our results are robust to common criticism on markup estimation and hold across several countries. These findings emphasize the specific role of labor market power for large firms, with significant

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[11]Raval (2023) uses a non-parametric cost share approach to estimate Cobb-Douglas production functions, which requires to assume perfectly competitive labor markets. To allow for labor market power, we instead estimate translog production functions using the same methodology as in the main specification, implemented by bins of the intermediate-to-labor expenditure ratio.

[12]Binned scatter plots projecting markups and markdowns on firm size are reported in Figure D.1 in online Appendix D. Table D.1 shows that the levels of markups and markdowns estimated accounting for labor-augmenting technology are similar to the baseline specification.

[13]Unfortunately, we cannot test these correlations with U.S. data because (i) publicly available and commercial datasets on U.S. companies do not disaggregate COGS and SG&A into labor and intermediate expenditure, and (ii) we cannot access restricted-use Census data due to residency requirements. We thus leave this extension to future research.

[14]Our sample includes the following countries: Belgium, Croatia, Czech Republic, Denmark, Finland, France, Germany, Hungary, Italy, Lithuania, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland. Each of them shows a negative and—with the exception of Denmark—significant sign in the cross-sectional correlation between markups and firm size. Furthermore, the correlation between markdowns and size is positive and significant for all countries.

implications for policy design, particularly because effective interventions may drastically differ depending on the source of market power being targeted.

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Appendix

A Details on the data

A.1 The AFiD database

We use rich firm-product-level panel data for the German manufacturing sector (1995-2016), supplied by the statistical offices of Germany. The data contain information on firms' employment, investment, revenue, and, most importantly, product quantities and prices at a ten-digit product classification. 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.

Data access. AFiD data, covering German manufacturing firms, 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".[15]

Variable definitions. The following list presents an overview of 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, 2022), 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

[15] 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.

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).[16]
- 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. 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.

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

[16]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.

require a time-consistent industry 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 (2022) 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 (2022). Table A.1 provides summary statistics for our final sample.

TABLE A.1. SUMMARY STATISTICS (AFID DATA)

	Mean	Sd	P25	Median	P75	Observations
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Markups	1.10	0.04	0.98	1.07	1.19	242,303
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

Note: Table A.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 microdata. 1995-2016.

A.2 The CompNet database

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 underlying firm population is truncated at a 20 employees cut-off. For a smaller set of countries, the data is also available without a size cut-off. Our results hold for the data without the size cut-off. All our results hold when focusing on countries including smaller firms. For the main analysis, we prefer the 20 employee sample because micro firms account for the vast majority of the business population, so including all firms gives little size variation along the sales distribution.

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

Table A.2 presents the yearly and sectoral coverage of the CompNet data for each country. For further information on the data, we refer to CompNet's User Guide (CompNet (2021)).[17]

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/.

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

Table A.2. Data coverage (CompNet data)

Country	(1) Years	(2) Excluded sectors	(4) Median employment
Belgium	2000-2018	None	37.32
Croatia	2002-2019	None	39.78
Czech Republic	2005-2019	None	58.40
Denmark	2001-2016	Real estate activities and ICT	35.00
Finland	1999-2019	Real estate activities	38.43
France	2004-2016	None	37.20
Germany*	2001-2018	None	56.67
Hungary	2003-2019	None	38.41
Italy	2006-2018	Real estate activities	36.15
Lithuania	2000-2019	None	40.03
Netherlands	2007-2018	Real estate activities	40.09
Poland	2002-2019	None	53.89
Portugal	2004-2018	None	35.60
Romania	2007-2019	Real estate activities	38.92
Slovakia	2000-2019	None	54.85
Slovenia	2002-2019	None	44.16
Spain	2008-2019	None	33.91
Sweden	2003-2019	None	36.88
Switzerland	2009-2018	None	73.70

Note: Table A.2 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 the 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.

B Bargaining Model

This section shows that we can derive the wage markdown formula also under a 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:

$$U(w_{it},\ L_{it}) = w_{it}\ L_{it} + (\ \overline{L}_{it} -\ L_{it})\overline{w}_{it}. \tag{B.1}$$

$\overline{w}_{it} \leq w_{it}$ is the reservation wage. $\overline{L}_{it}$ 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:

$$\max_{L_{it},\ M_{it}, K_{it}} \phi_{it} \log(\ L_{it}(w_{it} - \overline{w}_{it}) + (1-\phi_{it})\log(P_{it}Q_{it} - w_{it}L_{it} - z_{it}M_{it} - r_{it}K_{it}), \tag{B.2}$$

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

$$w_{it}\left(1 - \frac{\phi_{it}}{1-\phi_{it}} \frac{\Pi_{it}}{w_{it}L_{it}}\right) = MRP_{it}^{L}, \tag{B.3}$$

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 markups consistent with the markup rule in this framework.[18] This ensures that $MRP_{it}^{L} = \frac{P_{it}}{\mu_{it}} \frac{\partial Q_{it}}{\partial L_{it}}$. Combining this expression with the markup expression from the main text and the definition of the markdown ($\gamma_{it} = \frac{MRP_{it}^{L}}{w_{it}}$) yields the same estimator as equation (5) of the main text:

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

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

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

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 2022). We follow this interpretation.[19]

C Estimating output elasticities

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

Production model. The translog production model we apply writes:

$$q_{it} = \boldsymbol{\phi}'_{it}\boldsymbol{\beta} + \omega_{it} + \varepsilon_{it}. \tag{C.1}$$

Lower case letters denote logs. $\boldsymbol{\phi}'_{it}$ captures the production inputs, K_{it}, L_{it}, and M_{it}, and its interactions.[20] 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.[21] 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).[22]

There are three issues preventing us from directly estimating the production function (C.1) with OLS.

[19]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 (2024), 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.

[20]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.

[21]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.

[22]See also Appendix D.2.3 for how input shares relate to firm size.

- 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 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 purge firm revenue (for single- and multi-product firms) from price variation by deflating firm revenues with this price index.[23] Specifically, we construct firm-specific Törnqvist price indices for each firm's composite revenue from its various products:

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

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.[24]

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}.

Solving issue 2: Controlling for unobserved input price variation

[23]See also Smeets & Warzynski (2013) for an application of this approach.

[24]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.

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):

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

$B_{it}(.) = B_{it}\big((\pi_{it}, ms_{it}, G_{it}, D_{it}) \times \boldsymbol{\phi}_{it}^{c}\big)$ 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}). $\boldsymbol{\phi}_{it}^{c} = \{1; \tilde{\boldsymbol{\phi}}_{it}\}$, where $\tilde{\boldsymbol{\phi}}_{it}$ 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 $\tilde{\boldsymbol{\phi}}_{it}$ are not expressed in true quantities. The constant entering $\boldsymbol{\phi}_{it}^{c}$ highlights that elements of $B(.)$ enter the price control function linearly and interacted with $\tilde{\boldsymbol{\phi}}_{it}$ (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.[25] Although being restrictive, this assumption is more general than the ones employed in 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

[25] 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.

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.[26] Plugging (C.4) and the law of motion for productivity into (C.3) yields:

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

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).[27] 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.[28] We define identifying moments jointly for ε_{it} and ξ_{it}:

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

where $\boldsymbol{\Upsilon}_{it}$ 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:

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

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

[26] $\boldsymbol{T}_{it}$ and $\boldsymbol{\Gamma}_{it}$ 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.

[27] We approximate $h_{it}(.)$ by a third order polynomial in all of its elements, except for the variables in $\boldsymbol{\Gamma}_{it}$. Those we add linearly. $B_{it}(.)$ is approximated by a flexible polynomial where we interact the output price index with elements in $\tilde{\boldsymbol{\phi}}_{it}$ 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 $\tilde{\boldsymbol{\phi}}_{it}$ would create too many parameters to be estimated. This implementation is similar to De Loecker et al. (2016).

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

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

w_{it} denotes the average wage a firm pays.[29] We derive output elasticities from the production function as $\frac{\partial q_{it}}{\partial x_{it}} = \theta^X_{it}$ 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.[30] 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).[31]

D Additional results

D.1 CompNet data results

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. Notably, the data (and this analysis) includes also non-manufacturing as described in Appendix A.2. Using these joint distributions, we regress markups on firm size at the industry-year-size-quintile level:

$$\bar{\mu}_{kjt} = log(\overline{P_{\imath t} Q_{\imath t}})_{kjt} + \vartheta_j + \vartheta_t + \varepsilon_{kjt}. \tag{D.1}$$

$\bar{\mu}_{kjt}$ and $log(\overline{P_{\imath t} Q_{\imath t}})_{kjt}$ 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 D.1 shows binned scatter plots from running the regression described in Equation (D.1). Panel A shows a negative association between markups and firm size for every country (despite results are statistically insignificant for Denmark), whereas Panel B

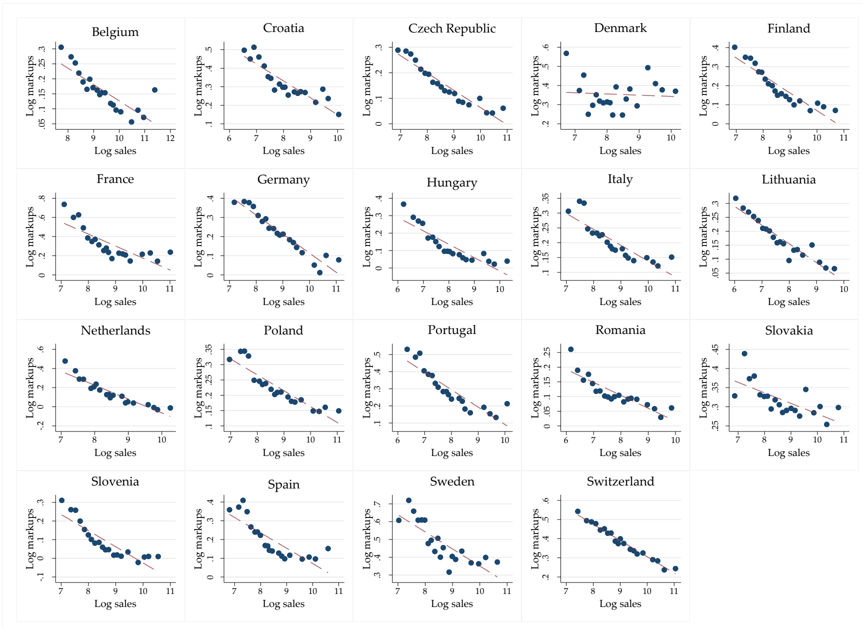
[29]The inclusion of output price information on the right-hand side of the production function also helps to address concerns about potential violations of the "scalar unobservability" assumption as discussed in Doraszelski & Jaumandreu (2020).

[30]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.

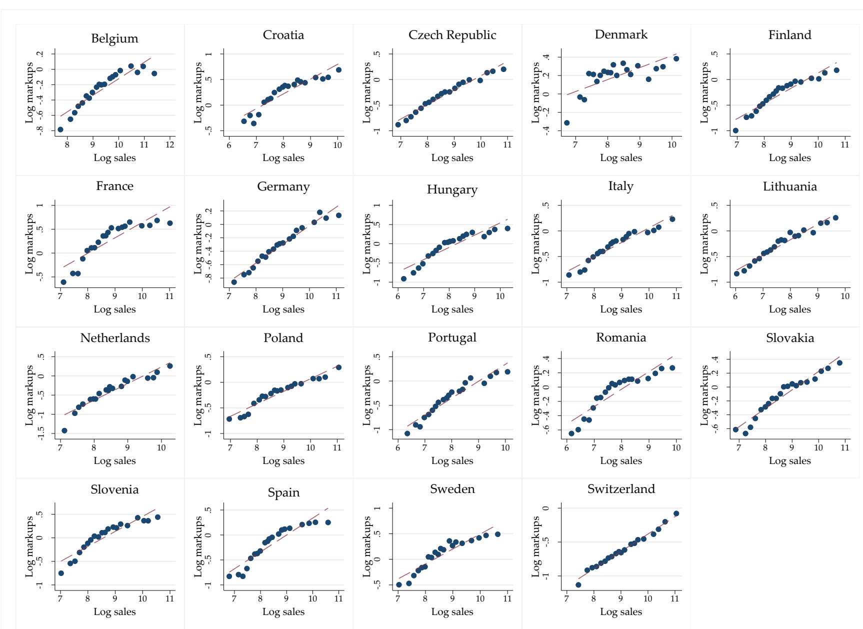
[31]We also do not purge measurement error and unanticipated shocks from output when estimating markups as this did not change our results (results with the error correction are available on request).

FIGURE D.1. MARKET POWER AND FIRM SIZE (COMPNET DATA)

Panel A. Markups and firm size.



Panel B. Markdowns and firm size



Note: Binned scatter plots from quintile-level regressions of median markups (Panel A) and markdowns (Panel B) on median firm size 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 A.2. All CompNet sectors as described in Appendix A.2.

reports a positive association between wage markdowns and firm size for every country in the data. For manufacturing only, also Denmark displays a statistically significant negative association between markups and size. These results are closely in line with the results from the German data.

D.2 Accounting for labor-augmenting technology

TABLE D.1. MARKUPS AND MARKDOWNS

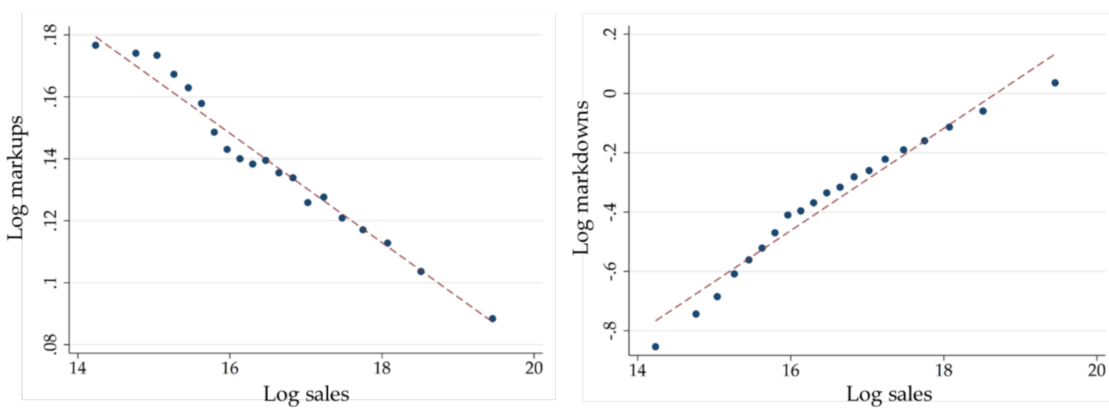
	Baseline specification			Accounting for labor augmenting technology		
	(1) mean	(2) median	(3) obs.	(4) mean	(5) median	(6) obs.
Markups	1.10	1.07	242,303	1.12	1.11	224,821
Markdowns	1.00	0.90	242,303	1.06	0.83	224,821

Note: Table D.1 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).

FIGURE D.2. MARKET POWER AND FIRM SIZE—ACCOUNTING FOR LABOR-AUGMENTING TECHNOLOGY

Panel A. Markups and firm size.

Panel B. Markdowns and firm size



Note: Binned scatter plots with year and industry fixed effects. Panel A (B) shows results from projecting markups (markdowns) on sales. Markups and markdowns are estimated accounting for labor-augmenting technology. German manufacturing sector data. 1995-2016. 224,821 firm-year observations.

D.3 Additional identification threats

Monopsony power in intermediates. Our approach to markup estimation requires a flexible input for which input prices are exogenous to firms. 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 (3)) 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; Treuren, 2025).

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

More importantly, unobserved adjustments costs in intermediates would strengthen our results as they artificially create a *positive* association between firm size and markups (Gamber, 2022). This can be seen from the markup Equation (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, we run regress markups on firm size for several firm groups. In Table D.2, we split firms based on their industry-classification into firms mainly producing i) consumer goods, ii) intermediate goods, and iii) investment goods.[32] 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 differences,

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

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

Table D.2. The markup-size correlation for subgroups of firms

Subgroup of firms	(1) Regression coefficient	(2) Number of observations
Consumer goods producers	-0.014*** (0.001)	64,998
Intermediate goods producers	-0.025*** (0.001)	102,324
Investment goods producers	-0.026*** (0.001)	73,752
Exporter	-0.020*** (0.001)	188,285
Non-Exporter	-0.027*** (0.001)	54,014

Notes: Table D.2 reports regression coefficients from projecting firm markups on firm size (sales) while controlling for year and industry fixed effects. 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.

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