Markup Dynamics Revisited:
Insights from a Survey of European Firms

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Abstract

Market power is a fundamental element of the economy and markups—defined as price over marginal cost—are the most used concept to study it. While recent advancements clarify under which conditions we can estimate markup levels and what type of bias we might encounter, it is often believed that time trends do not suffer from those biases. Leveraging a unique dataset, I challenge this prevailing assumption and uncover significant biases in markup evolution. I show that using standard techniques, one would overestimate the share of firms with increasing markups by more than 40 percentage points and that estimated markup dynamics are incorrect in more than 50% of cases. This critical finding not only casts doubt on the empirical methods used in markup analysis but also signals an urgent need for refined techniques that accurately capture market dynamics.

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JEL Codes: C14, C33, D24, E23, L11

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1 Introduction

Recent evidence on the rise in market power in the United States (De Loecker et al., 2020) and in the rest of the world (De Loecker and Eeckhout, 2018) has put markups at the center of the academic debate. This surge in market power has indeed been associated with the secular decline in the labor share (Autor et al., 2020), business dynamism (De Loecker et al., 2021), and consumer welfare (Edmond et al., 2023). Yet, existing literature points to methodological challenges in estimating markup levels from financial information (Bond et al., 2021). As with any study measuring unobservable components, there are no direct ways to validate the structural methodology to estimate markups, therefore the arguments are predominantly methodological or rely on simulated data (De Ridder et al., 2022, Raval, 2023).

This paper addresses these challenges by providing the first direct evidence on markup dynamics derived from survey data, thereby offering a unique validation of existing estimation methods. As part of the EFIGE project, a representative sample of European firms was asked if their margins had increased over the previous year. I use this data to infer markup dynamics as decreasing margins imply decreasing markups.[1] Hence, this is unique direct evidence on markup dynamics. I then compare these observations with changes over the same period resulting from markup estimates based on the production approach. The analysis reveals that for 54% of firms the estimated change is the opposite of what the firms actually declared, thus overestimating the share of firms with increasing markups by a conservative lower bound of 43 percentage points. This finding raises serious concerns about what the production approach can actually estimate and calls for a re-evaluation of the existing evidence of increasing market power.

During the onset of the Great Financial Crisis in 2008, survey data from the EFIGE project reveals that only 11% of firms across six major European countries reported an increase in margins. Although low, this number needs to be contextualized with the beginning of the Great Financial Crisis. Markups, on the other hand, are unobservable in the data. The production approach proposes to measure them as the product of output elasticity and inverse input share of a variable inputs (Hall, 1988, De Loecker and Warzynski, 2012). From this result, we can infer the change in markup from one year to the other from the change in output elasticity and in input share. Starting from a benchmark in which the production function does not vary over time, e.g. as it is with a Cobb-Douglas specification, I find that only 45% of firms have decreased the inverse input share in 2008. Hence, comparing it with survey data, we would overestimate the share of firms increasing markups by 45 percentage points. To account for time variation in output elasticities, I estimate a flexible production function using the control function approach of Olley and Pakes (1996). This method requires a number of additional assumptions on the market structure, the dynamics of productivity and what the econometrician can observe. Introducing time-varying output elasticities reduces the bias in the share of firms increasing markups by only 2 percentage

[1] This follows from the fact that if marginal cost growth exceeds price growth, then markups must fall; see Section 2 for a formal treatment.

points. Hence, this comparison highlights the challenges of estimating markup trends using the production approach.

Moreover, the data exhibit significant cross-country heterogeneity, likely reflecting varying economic conditions and firm conduct. Italy and Spain display the largest biases, while Germany and the United Kingdom show no significant difference between margin and markup dynamics. These variations underscore the importance of market-specific analyses and call for a critical reassessment of the evidence on rising market power.

This paper contributes to the literature on productivity estimation and markup using the production approach. Many papers have analyzed extensively the conditions to precisely measure markup levels (De Loecker et al., 2016, Gandhi et al., 2020, Bond et al., 2021, Raval, 2023), and some have proposed novel methods (Kirov et al., 2023). However, very little is known about the identification of time trends. Contemporaneous work by De Ridder et al. (2022) shows that the production approach correctly recovers time trends in simulated data and that revenue-based estimates evolve similarly to price-based ones. This paper provides the first direct evidence of time trends in markups and shows how the production approach suffers from a significant bias in estimating them.

2 How Did Margins Evolve Over Time?

This section examines the evolution of margins over time using a unique dataset that features survey information on margin dynamics. It begins with a detailed description of the data and then explains how these data can be used to infer markup dynamics.

2.1 The EFIGE Database

The primary data source for this study is the EU-EFIGE/Bruegel-UniCredit database (hereinafter, the EFIGE database), a unique and comprehensive dataset that combines extensive firm-level information for a representative sample of manufacturing firms across seven European countries.[2] Developed under the EFIGE project—supported by the European Commission—the database is designed to capture the manufacturing structure of each country through a stratified sampling approach. The sampling design stratifies by industry, region, and firm size, with an oversampling of larger firms (those with more than 250 employees) to ensure sufficient statistical power for that segment. Appropriate sample weights are provided to ensure that the retrieved statistics remain representative at the country and industry levels. Notably, the survey excludes firms with fewer than 10 employees.

The survey data in the EFIGE database were collected using a standardized questionnaire administered between January and April 2010, ensuring full comparability across countries.[3] The survey covers a broad range of topics—covering six modules: ownership

[2] Countries included are: Austria, France, Germany, Hungary, Italy, Spain, and the United Kingdom. Austria is dropped from the sample due to an insufficient number of observations for the empirical exercise carried out in the next section.

[3] The questionnaire was administered via CATI (Computer Assisted Telephone Interview) or CAWI (Computer Assisted Web Interview) procedures. The complete questionnaire is available on the Bruegel website: `https:`

Table 1: Changes in Margins between 2007 and 2008

	Increasing Margins (%)
France	0.127
Germany	0.135
Hungary	0.045
Italy	0.110
Spain	0.073
United Kingdom	0.212
Total	0.107

Notes: This table shows the share of firms with increasing margins based on survey responses. Survey weights are used to compute national averages.

structure, workforce composition, investment and innovation, market competition, and financial structure—with most questions referring to activities in 2008, and some extending to 2009 or earlier. This design enables a detailed picture of firm behavior during a critical period, including the onset of the Great Financial Crisis.

Following the collection of the survey data, the database has been integrated with balance sheet information from the Amadeus database by Bureau van Dijk covering the period 2001-2014. This integration provides 14 years of financial data for each surveyed firm and enables the computation of firm-specific indicators, including productivity and markup measures. Altomonte and Aquilante (2012) has shown that the sample aligns well with aggregate statistics for the countries in the analysis.[4] Table A.1 presents summary statistics for the entire period for which financial information is available.

2.2 Margins in Survey Data

The competition module of the EFIGE database provides survey responses regarding the evolution of margins. Specifically, I use responses on whether a firm's margins have increased, decreased, or remained constant between 2007 and 2008.[5] These responses are grouped into an indicator dummy that takes the value 1 for increasing margins and 0 otherwise.

Table 1 shows the share of firms reporting increased margins between 2007 and 2008. Only about 11% of the firm population reported an increase in margins over that period. Moreover, there is significant heterogeneity across countries, ranging from approximately 21% in the United Kingdom to only 5% in Hungary. These figures, among other factors, may reflect the cautious behavior of firms in the wake of the Great Financial Crisis. As discussed in the next section, the large share of firms with declining margins provides an ideal framework for studying markup dynamics.

`//www.bruegel.org/dataset/efige`.

[4]This database has already been used in numerous papers including Altomonte et al. (2013, 2016), Steinberg (2019), Pellegrino and Zingales (2017), Ferri et al. (2019).

[5]Figure A.1 shows the actual question in the questionnaire.

2.3 Mapping Margin Evolution to Markup Dynamics

Defining margins as prices minus marginal costs and markups as prices over marginal costs, a decline in margins implies a decline in markups. In particular, if margins fall, this indicates that the growth rate of marginal costs exceeds that of prices. Since markups are, by definition, greater than or equal to 1, this results in a decrease in markups. The following lemma formalizes this intuition.

Lemma 1. For every positive price $p > 0$ and marginal cost $c > 0$, let margins be the difference between price and cost, $M = p - c \geq 0$, and markups the ratio of price over cost, $\mu = \frac{p}{c} \geq 1$. If a firm's margin is decreasing, then its markup also decreases. Else, increasing margin can have ambiguous implications for markup and it is not possible to assess the sign of the markup change only from the margin.

Proof. Denote future price and cost as $p' = (1 + a)p$ and $c' = (1 + b)c$, with $|a| < 1$ and $|b| < 1$. We can expresses changes in margins and markups as:

$$\Delta M = M' - M = (p' - c') - (p - c) = ap - bc.$$

$$\Delta\mu = \mu' - \mu = \frac{p'}{c'} - \frac{p}{c} = \frac{(1+a)p - (1+b)p}{(1+b)c} = \frac{\mu}{\underbrace{(1+b)}_{>0}}(a - b).$$

While changes in margins and markups are complex elements depending on current variables and growth rates, here we focus only on the sign of the difference between future and present margins and markups. This will depend on price and cost growth rate as well as on the size of price and costs for margins. On the other hand, the sign of the change in markup depends only on growth rates. Consider the following two cases:

- Case 1: Decreasing Margins ($\Delta M \leq 0$). This implies that $\frac{p}{c} \leq \frac{b}{a}$. Since c cannot be larger than p (i.e., $\mu \geq 1$), it follows that $a \leq b$ and hence $\Delta\mu \leq 0$.
- Case 2: Increasing Margins ($\Delta M > 0$). This implies that $\frac{p}{c} > \frac{b}{a}$. In this case, the relation between a and b remains ambiguous, and it is not possible to deduce the sign of $\Delta\mu$ only from the change in margins.

□

In this paper, margins are interpreted as the difference between prices and marginal costs, so that markups are defined as the ratio of price to marginal cost. An alternative interpretation, sometimes used in practice, defines margins as the gross margin—sales minus total costs divided by sales (Anderson et al., 2025). Under the restrictive assumptions of constant returns to scale and no fixed costs, this alternative measure coincides exactly with markups.[6] More generally, however, the focus here is on the sign of the change in margins,

[6] While data on fixed costs are not readily available in EFIGE, or more in general in financial data, De Loecker et al. (2020) using overhead costs as a proxy find that their weighted average share of total costs decreases from 19.3% to 18.9% and their weighted average share of revenues decreases from 18% to 17.4% in 2008. Moreover,

which can be determined solely by comparing the growth rate of markups with that of the scale elasticity, i.e., the ratio of average costs to marginal costs. For a homothetic production function, the scale elasticity coincides with returns to scale. In such cases, a decline in gross margins implies that the markup growth rate is lower than the growth rate of returns to scale—a parameter that is often assumed to be constant over time. Therefore, even using this alternative interpretation of margins provides a simple mapping from the change in margins to the change in markups without imposing restrictive assumptions. The following lemma formalizes this intuition.

Lemma 2. Let gross margins be the difference between sales minus total costs divided by sales, $M = \frac{PQ - C(Q)}{PQ} \geq 0$, and markups the ratio of price over cost, $\mu = \frac{p}{c} \geq 1$. If a firm's gross margin is decreasing, then its markup also decreases if markup growth rate is lower than the scale elasticity growth rate.

Proof. Gross margins can be expressed as:

$$GM = \frac{PQ - C(Q)}{PQ} = 1 - \frac{AC(Q)}{P} = 1 - \frac{\kappa}{\mu},$$

where $C(Q)$ is the cost function and $\kappa = \frac{AC(Q)}{MC(Q)}$ is the scale elasticity, i.e., the ratio of average costs over marginal costs. Changes in gross margins are therefore:

$$\Delta GM = \left(\frac{\kappa}{\mu} - \frac{\kappa'}{\mu'} \right),$$

where κ' and μ' are future scale elasticity and markup. Denote $\mu' = (1+a)\mu$ and $\kappa' = (1+b)\kappa$, with $|a| < 1$ and $|b| < 1$. This implies that:

$$\Delta GM < 0 \;\Rightarrow\; a < b, \quad \text{and} \quad \Delta GM > 0 \;\Rightarrow\; a > b.$$

Thus, a decline in gross margins (i.e., $\Delta GM < 0$) implies that the markup growth rate is lower than the scale elasticity growth rate, leading to a decrease in the markup. □

3 Markups Evolution From Production Data

Markups, defined as the ratio of output price to marginal cost, are a key indicator of market power yet remain unobservable in the data (Ackerberg et al., 2015). This section employs the production approach—the most widely used method in macroeconomics—to infer markup dynamics from firm-level data.[7] Originally proposed by Hall (1988) for industry dynamics and refined by De Loecker and Warzynski (2012) for firm-level analysis, this structural method derives markups from firms' cost-minimization behavior without imposing demand-side assumptions or specific models of conduct or competition. In settings with heterogeneous

De Ridder (2024) proposes a method to estimate fixed costs from financial data; however, that method relies on correctly estimating markups using the production approach, which is precisely the subject of the present study, and therefore it is not applicable in this context.

[7] De Loecker and Syverson (2021) provides a review of the literature.

firms sourcing intermediate inputs from undistorted markets, the production approach yields a formula for markups that can be empirically implemented.

Firms have an idiosyncratic productivity, Ω_{it}, and produce combining a vector of flexible inputs, V_{it}, and a vector of nonflexible inputs, K_{it}, with a twice differentiable production function, $Q_{it} = Q_{it}(\Omega_{it}, V_{it}, K_{it})$. For sake of simplicity, I will consider a single flexible input and capital. Firms minimize per-period costs every period, with the following Lagrangian function:

$$\mathcal{L}(V_{it}, K_{it}, \lambda_{it}) = P^V_{it} V_{it} + r_{it} K_{it} + F_{it} - \lambda_{it}(Q(\cdot) - \bar{Q}).$$

Here, P^V is the price of the flexible input, r the user cost of capital, F any potential fixed costs, and λ the Lagrangian multiplier.[8] Crucially, the latter represents the local cost of relaxing the technological constraint, thus is a direct measure of marginal cost. Taking the first-order condition with respect to V yields

$$\frac{\partial \mathcal{L}(\cdot)}{\partial V_{it}} = P^V - \lambda_{it} \frac{\partial Q(\cdot)}{\partial V_{it}} = 0.$$

Multiplying both sides by the ratio of flexible inputs over revenue, $\frac{P_{it} V_{it}}{Q_{it} P_{it}}$, gives

$$\mu_{it} = \theta^V_{it} \frac{1}{s^V_{it}} \tag{1}$$

with θ^V_{it} being the output elasticity of input V, and $s^V_{it} = \frac{P^V_{it} V_{it}}{P_{it} Q_{it}}$ the input share.

This expression for markups can be measured in the data. Specifically, the markup is expressed as the product of output elasticity and the inverse input share of the flexible input. While the inverse input share is readily available in numerous datasets, output elasticities are unobservable and notoriously challenging to estimate (Ackerberg et al., 2015). Nonetheless, output elasticities are crucial for determining the level of markup since they capture the way firms mix their inputs. However, our focus is on understanding the *change* in markups over time. If the production function remains unchanged, variations in markups will be reflected only in the input shares.

Table 2 presents the share of firms by country with decreasing margins alongside the share with decreasing inverse flexible input share (primarily materials, as labor adjustments in Europe are less flexible and not cost-free). This comparison reveals a critical insight: conventional methods that assume constant output elasticities over time significantly underestimate the number of firms with diminishing markups. While approximately 90% of firms experienced reduced margins between 2007 and 2008, markup estimations suggest that only about 45% did, indicating a substantial 45 percentage point bias. This figure is very conservative and likely represents a lower bound, as additional mismatches may occur among firms reporting increasing margins (Lemma 1). Notably, although this bias is significant in

[8] I abstract for market power in input markets in this setting. Evidence and analysis of this can be found in a growing literature including De Loecker et al. (2016), Kirov and Traina (2022), Mengano (2022), but are outside of the scope of this paper.

Table 2: Changes in Margins and Input Share

	Decreasing Margins (%)	Decreasing Input Share^{-1} (%)	Δ
France	0.854	0.569	-0.285***
Germany	0.846	0.486	-0.360***
Hungary	0.973	0.534	-0.439***
Italy	0.878	0.423	-0.456***
Spain	0.932	0.421	-0.511***
United Kingdom	0.799	0.520	-0.279***
Total	0.893	0.445	-0.448***

Notes: This table shows the share of firms with decreasing margins and inverse flexible input share. The first column is based on survey responses, the second on financial data and the third compute the difference in percentage points. Survey weights are used to compute national averages.

every country, its magnitude varies, with France and the United Kingdom exhibiting the smallest biases and Italy and Spain the largest.

I now relax the assumption that output elasticities do not change over time. In this regard, I assume that firms produce with the following translog production function, expressed in logs:

$$q_{it} = a_{it} + \beta^L l_{it} + \beta^M m_{it} + \beta^K k_{it} + \beta^{LL} l_{it}^2 + \beta^{MM} m_{it}^2 + \beta^{KK} k_{it}^2 + \beta^{LK} l_{it} k_{it} + \beta^{LM} l_{it} m_{it} + \beta^{KM} k_{it} m_{it} + \beta^{LKM} l_{it} k_{it} m_{it}. \tag{2}$$

In this setting, the output elasticity becomes a function of parameters and endogenous variables:

$$\theta_{it}^V = \beta^M + 2\beta^{MM} m_{it} + \beta^{LM} l_{it} + \beta^{KM} k_{it}. \tag{3}$$

These elasticities are firm-specific and vary over time. I can take firm's intermediate inputs, workforce and capital directly from the financial data in the EFIGE database. However, the parameters governing the production function are not observable, thus I adopt the control function approach initially proposed by Olley and Pakes (1996) and recently used in numerous papers in the macroeconomic literature (e.g. De Loecker et al. 2020, De Ridder et al. 2022, Burstein et al. 2020). The details about the estimation are left in Appendix B.

Table 3 reports the share of firms by country with decreasing margins alongside the share with decreasing markups, building on the previous analysis where changes in the inverse input share served as a proxy for markup changes. In this more comprehensive analysis, markups are directly estimated by also accounting for variations in output elasticities.

Overall, the table shows significant discrepancies between the proportions of firms experiencing declines in margins versus those with decreasing markups. On average, while 89.3% of firms across the surveyed countries report reduced margins, only 46.7% exhibit a corresponding decline in markups. This average disparity of 42.6 percentage points under-

Table 3: Changes in Margins and Markups

	Decreasing Margins (%)	Decreasing Markups (%)	Δ
France	0.854	0.509	-0.345***
Germany	0.846	0.725	-0.121
Hungary	0.973	0.572	-0.401***
Italy	0.878	0.434	-0.444***
Spain	0.932	0.454	-0.478***
United Kingdom	0.799	0.810	0.011
Total	0.893	0.467	-0.426***

Notes: This table shows the share of firms with decreasing margins and markups. The first column is based on survey responses, the second on estimates following Ackerberg et al. (2015) using financial data and the third compute the difference in percentage points. Survey weights are used to compute national averages.

scores two key points: first, the limitations of conventional markup estimation techniques in capturing time evolution; and second, the limitations of relying solely on proxies such as the inverse input share. Indeed, the difference in the share of firms with decreasing markups remains essentially unchanged when allowing for more flexible production functions rather than assuming a fixed technology.

Examining individual countries reveals substantial heterogeneity. For instance, in France, 85.4% of firms report decreased margins compared to only 50.9% showing a decline in markups—a difference of 34.5 percentage points. Similar large disparities are evident in Hungary, Italy, and Spain, with Spain exhibiting a remarkable 47.8 percentage point difference. In contrast, when changes in output elasticities are incorporated, the results for Germany and the United Kingdom converge, with both countries displaying nearly identical percentages of firms reporting decreases in margins and markups. This contrast highlights the nuanced impact of different methodological approaches and emphasizes the importance of considering multiple market-specific factors in markup estimation.

3.1 From Macro to Micro.

Thus far, the analysis has focused on the aggregate behavior of firms, examining the share of firms that experience increases or decreases in profitability. Now, the focus shifts to individual firm behavior. Table 4 reports the percentage of firms for which the sign of the change in margins, as reported in the survey, matches the sign of the change in estimated markups.[9] This micro-level analysis reveals a significant disconnect between the survey data and the estimation results regarding changes in margins and markups. Overall, only 45.9% of firms across all countries exhibit matching directions in margin and markup changes—45.6% when considering only firms with decreasing margins—indicating a substantial divergence for the majority of firms.

Country-specific results also vary notably. Germany exhibits the highest alignment, with

[9]Results are shown only for markups computed with time-varying elasticities.

Table 4: Micro Dynamics in Margins and Markups

	Matched Δ (%)	Matched Negative Δ (%)
France	0.506	0.498
Germany	0.719	0.646
Hungary	0.561	0.546
Italy	0.426	0.432
Spain	0.449	0.448
United Kingdom	0.788	0.644
Total	0.459	0.456

Notes: This table shows the share of firms for which the sign of the change in margins and markups is the same. The second column shows the same statistics conditional on decreasing margins.

71.9% of firms showing matched changes, suggesting a closer correlation between margins and markups. In contrast, Italy and Spain display the lowest alignment, at 42.6% and 44.9% respectively, indicating a more pronounced disconnect in these economies. The United Kingdom also presents interesting results, particularly among firms with decreasing margins.

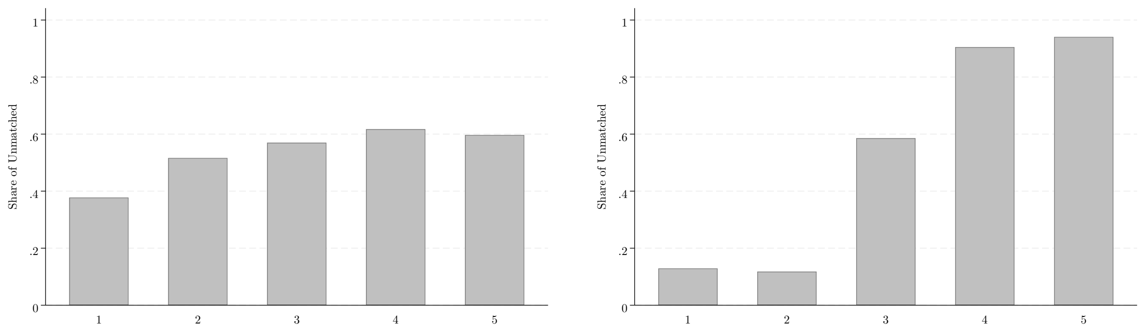
3.2 Bias Relevance.

Finally, I examine the bias in the estimated markup dynamics by investigating which parts of the markup distribution are the most affected. The analysis focuses on whether the bias is concentrated around zero changes—in which case, any mismeasurement might be less concerning—or whether it is more pervasive. The evidence in Figure 1 suggests a different pattern.

Figure 1a shows that, when examining markup levels, the distribution of unmatched dynamics is consistent across all quintiles. This uniformity indicates that the bias is not systematically related to the absolute level of markups; errors are not predominantly clustered around a specific value (e.g., a markup of 1). Instead, the bias appears to impact a broad range of markup levels. Moreover, Figure 1b reveals that, when focusing on changes in markups, the estimated dynamics tend to overstate the proportion of firms that are increasing their market power. Notably, this overestimation is not centered around zero but is skewed toward larger increases in markups.

This pattern implies that the bias is not merely a minor misclassification error but represents a significant distortion that overstates the trend of rising market power. Consequently, these findings challenge the common assumption that the bias in markup estimation is negligible and underscore the necessity for more accurate estimation methods when analyzing markup dynamics, given their substantial implications for understanding market power trends.

Figure 1: Bias Along the Distribution



(a) Unmatched by Markup Quintile

(b) Unmatched by Δ Markup Quintile

Notes: These figures show the percentage of firms with unmatched dynamics in margins and markups. Panel (a) compares it by quintile of the markup distribution, while panel (b) along quintiles of the Δ markup distribution.

4 Conclusions

This study leverages unique survey data to critically assess the reliability of the prevailing production-based methodology for estimating markups—a cornerstone of market power analysis. The evidence indicates substantial biases in the traditional approach. By comparing survey-based margin changes with production-based estimates for the 2007-2008 period, the analysis reveals that the conventional method overstates the share of firms experiencing increases in markups. Specifically, while production-based estimates suggest that over 50% of firms exhibit rising markups, survey data indicate that fewer than 11% do. These findings corroborate recent concerns regarding the complexities and potential inaccuracies inherent in the production approach (see, e.g., Kirov et al., 2023, Bond et al., 2021, Raval, 2023).

Although prior research has predominantly focused on the levels of markups, this study emphasizes the critical importance of understanding their dynamics. The significant biases uncovered here not only compromise the accuracy of markup levels but also misrepresent the underlying trends in markup evolution. This misrepresentation calls into question the reliability of existing evidence on rising market power and its broader economic implications.

Addressing these methodological shortcomings represents a promising avenue for future research. Refining and developing more robust methods for markup estimation is essential to bridge the gap between theoretical models and empirical realities. Enhanced estimation techniques will provide deeper insights into the interplay between market forces, firm behavior, and economic outcomes, thereby supporting more informed policy decisions and a richer understanding of the role of market power in the economy.

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A Additional Tables and Figures

Table A.1: Summary Statistics (2001-2014)

	Mean	Median	No. obs
Sales	14,246.36	3,746.47	93,517
Capital	2,796.39	606.78	93,517
Materials	7,841.56	1,591.05	93,517
Employment	61.84	26.00	93,517

Notes: This table shows summary statistics for the sample of analysis. Sales, capital and materials are in thousands EUR deflated using GDP deflators, while employment is the number of employees.

Figure A.1: Questionnaire Snapshot

E11. During the last year, the size of your margin has:
- Increased
- Decreased
- Remained constant

B Estimating Output Elasticities

Estimating the firm production function, in this case Equation (2), is challenging, since firm productivity is not observed resulting in an omitted variable bias. More specifically, firm productivity crucially drives all firm actions, including input choices, and firm output, thus the bias becomes a simultaneity bias.

To tackle this issue, I use the control function approach (Olley and Pakes, 1996). I start by noting that log productivity, a, can be divided in two additive terms, firm TFP ω and a shock commonly considered a measurement error ε. Only the first one is relevant for firm behavior.

At the basis of the control function approach is the idea of finding a function to control for the omitted variable, productivity. In this setting, the chosen function is input demand. Indeed, given that firms use productivity to decide the amount of inputs to buy, this gives a straightforward representation as $m = m(\omega, \Lambda)$, with Λ representing the remaining state variables that firms use to take decision on inputs. As long as this function is increasing in ω, meaning that more productive firms demand more intermediate inputs, and that firm productivity is the only unobservable firm characteristic, it can be inverted and used to control for productivity, i.e. $\omega = m^{-1}(m, \Lambda)$ Therefore, we can rewrite the production function as:

$$q_{it} = m^{-1}(m_{it}, \Lambda_{it}) + \boldsymbol{\beta}^\top \mathbf{x}_{it} + \varepsilon_{it}.$$

where $\boldsymbol{\beta}$ is a vector with all production function parameters, and $\mathbf{x}_{it}$ is a vector of all inputs and their interactions that enter Equation (2).[10]

The first step of the estimation procedure therefore consists in estimating this equation by flexibly approximating the inverse input demand with a polynomial approximation. Therefore, it estimates the following equation:

$$y_{it} = \Phi_{it} + \varepsilon_{it}, \tag{B.1}$$

where Φ_{it} is a combination of all the terms of the production function and of the approximation of the input demand. While it is not possible to recover any parameter from the production function, it allows to estimate the error term and to get the predicted output, $\hat{y}$.

The second step exploits the (assumed) first-order Markov process for productivity:

$$\omega_{it} = g(\omega_{it-1}) + \xi_{it}. \tag{B.2}$$

Combining the results from the first step and Equation (B.2) gives a non-linear equation that can be estimated:

$$\hat{\Phi}_{it} - \boldsymbol{\beta}^{\top}\mathbf{x}_{it} = g(\hat{\Phi}_{it-1} - \boldsymbol{\beta}^{\top}\mathbf{x}_{it-1}) + \xi_{it}$$

where also in this case the function $g(\cdot)$ can be flexibly approximated. Assuming that TFP follows an AR(1) process with the parameter ρ governing the persistence, it is possible to construct the following set of moment conditions to estimate the output elasticities:

$$\mathbb{E}\left[\xi\left(\boldsymbol{\beta}, \rho\right) \times \mathbf{z}\right] = \mathbf{0} \tag{B.3}$$

where $\mathbf{z}$ is the set of admissible instruments consistent with the structural model and includes lagged intermediate inputs as well as current and lagged values of labor and capital.

I use this methodology to estimate the function separately for the manufacturing industry in each country. The available data does not contain sufficiently detailed sector information to allow for a more granular estimation. Consequently, I assume that the deep parameters governing the production process are common within the manufacturing industry.

[10] Formally, $\boldsymbol{\beta}$ is defined as: $\boldsymbol{\beta} = \left[\beta^{L},\quad \beta^{M},\quad \beta^{K},\quad \beta^{LL},\quad \beta^{MM},\quad \beta^{KK},\quad \beta^{LK},\quad \beta^{LM},\quad \beta^{KM},\quad \beta^{LKM}\right]^{\top}$, and $\mathbf{x}_{it}$ as: $\mathbf{x}_{it} = \left[l_{it},\quad m_{it},\quad k_{it},\quad l_{it}^{2},\quad m_{it}^{2},\quad k_{it}^{2},\quad l_{it}k_{it},\quad l_{it}m_{it},\quad k_{it}m_{it},\quad l_{it}k_{it}m_{it}\right]^{\top}$.