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Evolution of Markups in the Manufacturing Industry of Turkiye*

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Abstract

In this study, we aim to estimate the labor markups along with the evolution of labor and profit shares in the manufacturing industry of Turkiye over 2007-2021 via an administrative firm-level dataset, Entrepreneurship Information System (EIS), covering the universe of firms and containing detailed balance sheet information. We employ the recently popularized technique, the production function approach developed by De Loecker and Warzynski (2012), to estimate markups. Until 2016, there is a general decline in the level of markups. Concurrently, the gross profit rate slightly increases, and labor share in value added remains relatively stable. However, since 2016, which corresponds to the era of high inflation, there has been a notable surge in gross profit rates alongside a significant decrease in the labor share. The primary catalyst for these post-2016 shifts is attributed to firms positioned in the upper percentiles of the markup distribution, which successfully increased their markups and their share in total value-added during this period. As such, it may be fruitful for the competition policy to delve deeper into the root causes of the post-2016 surge in the markups of the high markup firms as well as the changing market composition.
Keywords: markup, market power, profits
JEL Codes: D22, D43

1. Introduction

Examining the dynamics of markups within a market or industry provides valuable insights into the level of competition and the distribution of economic gains between firms and consumers. In the case of Turkiye, understanding markup trends holds particular significance due to the country's unique market structure and ongoing economic developments of high inflation.

Understanding markups during periods of inflation is crucial for policymakers, economists, and consumers alike. Inflation erodes the value of money, and markups play a significant role in determining how inflationary pressures are transmitted throughout the economy. By studying how markups change over time during inflation, we can gain insights into whether firms are passing on increased costs to consumers through higher prices or absorbing some of those costs themselves. This information is critical for designing policies to stabilize prices and protect consumers from the adverse effects of inflation. Moreover, understanding markup dynamics reveals potential sources of market power, giving policymakers tools to identify and address competitive imbalances or anti-competitive practices that could exacerbate inflationary pressures.

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From 2010 onwards, Turkiye experienced a period of relatively subdued inflation compared to its historical trends, often aligning with global patterns. During the early 2010s, inflation generally remained within single digits, mirroring trends in many developed economies. However, in recent years, Turkiye has witnessed a more volatile inflationary yield with sharp spikes driven by factors such as currency depreciation, global commodity price fluctuations, and domestic economic policies. The yearly inflation rate in Turkiye as of February 2024 was 67.07%. Inflation set a two-decade record high in 2022 with more than 84% in contrast with many developed economies, which have generally exhibited more moderate inflation levels (Turkish Statistical Institute (TurkStat)).

At the time of this study, the most recent data available was for the year 2021. Although the inflation rate in Turkey experienced sharp spikes during the years 2022 and 2023, the average inflation rate spanning from 2017 to 2021 was nowhere near low. According to TurkStat, the consumer price index surged by 229% during this period, indicative of an average annual inflation rate of 18%. Consequently, we posit that our findings offer valuable insights into the dynamics of markups amidst periods of high inflation.

While several established methods exist for markup estimation, each has strengths, limitations, and specific data requirements. The accounting approach offers simplicity, relying on calculating average costs as a proxy for marginal costs. However, it rests on solid assumptions such as zero fixed costs and constant returns to scale, which may not always hold in practice. In contrast, the demand approach allows for more flexibility, employing the first-order conditions of firm profit maximization and price elasticity of demand to infer markups. However, this method necessitates reliable data on prices and quantities of individual products for a well-defined set of firms – data that can be challenging to obtain, especially for studies spanning numerous firms and a long time horizon.

"The production function approach," pioneered by Hall (1988) and refined by De Loecker and Warzynski (2012), presents a powerful alternative by departing from the firm's cost minimization problem. By imposing a value-added quantity constraint, this approach ingeniously uses the Lagrange multiplier associated with the constraint to represent the firm's unobserved marginal cost. With estimations of input elasticities via production function estimation techniques and observable labor share data, firm-specific markups can be calculated over time.

To examine markup trends in the Turkish manufacturing industry, this study leverages a unique administrative, firm-level dataset provided by the Turkish Ministry of Industry and Technology. The Entrepreneurship Information System (EIS) offers rich information on enterprise registers, balance sheets, employee records, and more for 2006-2021. Using a carefully constructed sample, we derive essential metrics such as output, value-added, and capital stock. Our primary markup estimation relies on the flexible Translog production function, estimated using the Levinsohn and Petrin (2003) method with Ackerberg, Caves, and Frazer (2015) correction. The choice of a Translog specification allows us to capture potential non-linearities and generate firm-specific input elasticities crucial for accurate markup calculations. Results derived from a Cobb-Douglas production function serve as a robustness check.

This study unveils the dynamic fluctuations of markups as well as labor and profit shares in the Turkish manufacturing sector. Utilizing a data-driven, firm-level approach, we uncover a U-shaped trajectory for the firms located at the upper percentiles of the markup distribution: initial decline followed by a post-2016 surge, which corresponds to the era with high inflation. The remaining firms also experienced a decrease in their markups until 2016, but thereafter, their markups remained relatively stable. As of 2016, there is a sharp decrease in the labor share and a corresponding significant increase in the profit rate. Notably, the expansion and the rise in the markups of high-markup firms fueled these post-2016 changes, highlighting the crucial role of firm heterogeneity.

Related literature. Using markups as a market power metric has gained prominence within industrial organization research. Hall's (1988) methodology for deriving markups from aggregate data and De Loecker and Warzynski's (2012) firm-level adaptation have been foundational to this focus. De Loecker et al. (2020), an influential study on the US economy, spurred extensive research into markups and market power across various economies.

Studies point to a concerning upward trend in average markups worldwide. Several analyses (De Loecker and Eeckhout, 2018; Hall, 2018; Calligaris et al., 2018; Diez et al., 2018; Diez et al., 2019; Akcigit et al., 2021; De Loecker et al., 2020) document significant increases over the past few decades. This escalation in markups appears more pronounced in advanced economies compared to emerging markets (De Loecker and Eeckhout 2018; Diez et al., 2018; Diez et al., 2019; Akcigit et al., 2021). The observed rise in markups is mainly attributable to firms already possessing the highest markup levels (De Loecker et al., 2020; Calligaris et al., 2018).

While research consistently signals upward markup trends, variations in estimation methods exist. Weche and Wambach (2018) report notably higher markup figures for the EU than other literature, e.g., the markup figures of De Loecker et al., (2020) for the US. Additionally, several studies investigate markups at a country-specific level, providing insights specific to Germany, Belgium, Japan, France, Norway, the UK, Italy, and others.

Research specific to Turkey's economic performance often centers on profit metrics, but studies examining markups exist. According to Taymaz and Yilmaz (2015), average markup increases in the Turkish manufacturing sector until 1994, followed by a post-EU Customs Union decline. Unveren and Sunal (2015) show that high markups are a primary factor driving Turkey's low labor share. Akcigit et al. (2020) showed that post-2012 increases in markups observed in Turkey's manufacturing industry, predominantly driven by large firms. Yilmaz and Kaplan (2022) confirm that large firms significantly influence overall markup trends within Turkey's manufacturing sector. Pismaf (2003) works on market power and markups in Turkiye (2006-2021) using a cost approach rather than the production approach we use in this paper. The author finds that markups have tended to rise since 2014. This is driven mainly by the rise in markups of large firms. The author also finds a positive correlation between markups and inflation, but the direction of causality seems unknown. Within the extended literature, this paper suggests similar findings regarding markups in the manufacturing sector employing the production function approach using unique firm-level data for the first time.

2. Data and Methodology

The main challenge associated with markup estimation is that the marginal costs (and mostly output prices) are not observable. The so-called accounting approach assumes that the average costs are equal to marginal costs and, therefore, recovers markups by dividing the total revenue by total costs. Whereas recovering markups via the accounting approach is straightforward, this approach rests on solid assumptions such as zero fixed costs and constant returns to scale.

The industrial organization literature, on the other hand, imposes a specific demand system and a competition structure. Markups can then be estimated by utilizing the first-order conditions of firms' profit maximization problem and the price elasticity of demand. See, for example, Berry et al. (1995) among others. Whereas this approach is powerful for estimating the markups of well-defined, specific industries during short periods, it is somewhat restrictive if the purpose is to estimate markups for large industries and over more extended time periods. Furthermore, the demand approach requires prices and quantities of goods sold to be observed, which is again impossible when the interest is on larger sets of firms over several years.

Building upon the insights of Hall (1988), the production function approach developed by De Loecker and Warzynski (2012) avoids these issues by departing from a simple cost minimization problem. Let the cost minimization problem of a firm i, at time t be given by:

$$\min_{L_{i,t}, K_{i,t},} w_{i,t}L_{i,t} + r_{i,t}K_{i,t} \tag{1}$$

where $w_{i,t}$ and $r_{i,t}$ respectively represent the prices of factor inputs labor, $L_{i,t}$, and capital, $K_{i,t}$. Imposing a value-added quantity constraint[3] $q(\sigma_{i,t}, L_{i,t}, K_{i,t}) \geq \bar{q}$, where $\sigma_{i,t}$ is an unobserved productivity shock, the Lagrangean associated with the cost minimization problem is:

$$\mathcal{L}(L_{i,t}, K_{i,t}, \lambda_{i,t}) = w_{i,t}L_{i,t} + r_{i,t}K_{i,t} - \lambda_{i,t}(q_{i,t}(\sigma_{i,t}, L_{i,t}, K_{i,t}) - \bar{q}). \tag{2}$$

The production function approach builds on the insight that the Lagrange multiplier associated with the value-added constraint, $\lambda_{i,t}$, represents the marginal cost, i.e., the effect of a marginal relaxation of the constraint on the objective function (total costs). First-order-condition with respect to labor supply reads:

$$w_{i,t} = \lambda_{i,t} \frac{\partial q_{i,t}(\sigma_{i,t}, L_{i,t}, K_{i,t})}{\partial l_{i.t}}. \tag{3}$$

[3] The production function approach can also be utilized by incorporating intermediate goods into the production function and assuming that q represents output instead of the value-added. Because our focus is on estimating labor markups, employing a value-added production function with labor and capital as factor inputs is sufficient.

Multiply both sides of (3) by $l_{i,t}/q_{i,t}(\sigma_{i,t}, L_{i,t}, K_{i,t})$ and the right-hand-side by the ratio of value-added price to itself, $P_{i,t}/P_{i,t}$, to get:

$$\frac{w_{i,t}L_{i,t}}{q_{i,t}(\sigma_{i,t}, L_{i,t}, K_{i,t})} = \frac{P_{i,t}}{P_{i,t}}\ \lambda_{i,t}\frac{\partial q_{i,t}(\sigma_{i,t}, L_{i,t}, K_{i,t})}{\partial L_{i,t}}\frac{L_{i,t}}{q_{i,t}(\sigma_{i,t}, L_{i,t}, K_{i,t})}. \tag{4}$$

Recognizing that markup is the price-marginal cost ratio, $\frac{P_{i,t}}{\lambda_{i,t}} = \mu_{i,t}$, and rearranging equation (4) yields:

$$\mu_{i,t} = \delta_{i,t}^{q,L}\frac{P_{i,t}q_{i,t}(\sigma_{i,t}, L_{i,t}, K_{i,t})}{w_{i,t}L_{i,t}} \tag{5}$$

where the first term $\delta_{i,t}^{q,L} = \frac{\partial q_{i,t}(\sigma_{i,t}, L_{i,t}, K_{i,t})}{\partial L_{i,t}}\frac{L_{i,t}}{q_{i,t}(\sigma_{i,t}, L_{i,t}, K_{i,t})}$ represents the elasticity of value added with respect to labor supply and the second term is the inverted share of labor in value-added.[4] Since the latter term is directly observable in many firm-level datasets and the former term can be estimated via the well-known production function estimation techniques, firm-specific markups be recovered at any year.

We utilize an administrative, firm-level, employee-employer integrated dataset provided by the Ministry of Industry and Technology of Turkiye's Entrepreneurship Information System (EIS). EIS covers the universe of registered firms over 2006-21 and provides detailed information on enterprise registers, balance sheets, employee registers, and between-firm sales, among other firm-specific aspects. Although the first year of the dataset is 2006, our markup series begins in 2007 since stock adjustments and depreciation calculation require information on the prior year.

Utilizing mainly enterprise registers, balance sheets, and employee registers, we construct output, input, value-added, labor cost, annual hours worked, depreciation, gross profit, and capital stock variables. Our sample size of the manufacturing industry starts at approximately 70.000 in 2007 and exceeds 120.000 in 2021. Firms employ 29 individuals on average. Table 1 provides some further descriptive statistics of our sample. Gross profit rates are calculated by dividing gross profits by output. Thus, gross profit share and gross profit rate are used interchangeably throughout this study. Labor share simply indicates the ratio of labor costs to value added. See Appendix Section A for further details on data preparation and variable construction.

[4] As in De Loecker and Warzynski (2012), the monetary value of total value added is adjusted for the error term to reflect planned value-added. See Appendix for further details.

Table 1. Descriptive statistics per firm (in million TL, annual)

Year	Output	Input	Value-added	Labor Cost	Depre-ciation	Gross Profit	Sample Size
2007	5.12	4.11	1.01	0.42	0.21	0.38	71.392
2008	5.68	4.54	1.14	0.45	0.20	0.49	75.395
2009	5.12	4.02	1.10	0.47	0.21	0.42	75.054
2010	6.11	4.92	1.20	0.54	0.21	0.44	77.925
2011	7.75	6.26	1.49	0.61	0.24	0.64	82.148
2012	7.88	6.43	1.46	0.69	0.24	0.53	87.069
2013	8.35	6.67	1.68	0.75	0.27	0.66	93.102
2014	9.16	7.31	1.85	0.85	0.29	0.72	98.902
2015	9.73	7.56	2.17	0.98	0.31	0.88	104.418
2016	10.36	7.90	2.46	1.16	0.34	0.96	108.286
2017	13.10	10.06	3.04	1.30	0.38	1.36	110.815
2018	16.71	12.79	3.92	1.48	0.47	1.97	116.534
2019	18.40	14.52	3.88	1.63	0.53	1.71	117.656
2020	20.59	15.82	4.77	1.69	0.57	2.51	123.462
2021	37.09	27.65	9.45	2.46	1.86	5.13	121.649

Notes: Construction of the variables is described in Appendix Section A. Figures represent per firm (total divided by the number of firms), annual values in million TL.

EIS provides us with the inverted share of labor in value-added, i.e., the second term in equation (5), for each firm every year. Recovering the first term, i.e., elasticities of factor inputs requires estimating a production function. We separately estimate a Translog and a Cobb-Douglas production function by employing the Levinsohn and Petrin (2003) method combined with Ackerberg, Caves and Frazer (2015) correction. See Appendix Section B for a detailed account of our production function estimation procedure. We prefer the Translog production function as our main specification due to its flexibility, i.e., it produces firm-specific input elasticities and performs better in capturing nonlinearities in input-output relationships. See Table 2 for the elasticities produced by the Translog production function estimation. The elasticities reported in Table 2 represent firm-specific elasticities averaged across firms and years. The results of the Cobb-Douglas production, which fundamentally produces the same implications as the Translog function, are reported in Appendix Section C.

Table 2. Translog production function estimation results

NACE Code	Market Share	Labor Elasticity	Capital Elasticity	Returns-to-scale
Avg.	-	*0.828*	*0.159*	*0.986*
10	0.142	0.749	0.149	0.898
24	0.120	0.882	0.176	1.058
29	0.091	0.772	0.150	0.922
13	0.085	0.798	0.153	0.951
25	0.059	0.850	0.186	1.036
20	0.056	0.968	0.137	1.105
27	0.056	0.774	0.135	0.909
22	0.054	0.946	0.145	1.091
14	0.054	0.760	0.110	0.870
28	0.049	0.829	0.164	0.993
23	0.048	0.822	0.250	1.072
19	0.043	0.964	0.178	1.141
17	0.027	0.848	0.167	1.015
31	0.018	0.784	0.131	0.916
26	0.014	0.869	0.144	1.012
32	0.014	0.715	0.136	0.850
16	0.013	0.793	0.146	0.940
21	0.013	0.872	0.183	1.055
33	0.012	0.763	0.163	0.926
30	0.011	0.904	0.153	1.057
15	0.008	0.750	0.124	0.873
11	0.007	0.927	0.226	1.154
18	0.007	0.698	0.142	0.840

Notes: Sectors are ranked based on their market share within the manufacturing industry. Sector definitions can be found in Table 3 of the Appendix. As explained in the text, the translog production function produces elasticity estimates at the firm level. Firm-level estimates are averaged within industries, across firms, and years to produce the figures reported in the table. The first row presents the average elasticities and returns-to-scale across manufacturing industries.

3. Results

Using the EIS data and production function approach, we find that labor shares in Turkiye have a tendency to fluctuate but have a decreasing trend after 2016, with a slight increase in 2019 and a sharp fall from 2019 to 2021. Meanwhile, Figure 1 also shows that gross profit share in output only slightly increased from 2012 to 2016. After 2016, however, it sharply increased, accompanying the decline in the labor share. Although the labor share fluctuates around 0.4 and 0.45, Turkiye experienced a sharp fall in labor share to around 0.25 in 2021. The decreasing trend in labor share and increasing trend in gross profit share in Turkiye, especially after 2016, could come from the fact that firms are exercising greater market power. Prices might rise beyond marginal costs, generating extra profits beyond workers' share, hinting at a fall in competition. The second explanation could be the change in the production composition towards high markup firms. Our analyses below suggest that both explanations play some part.

Figure 1. Labor and profit shares

Figure 2 illustrates the evolution of markups for the firms located at different percentiles of the markup distribution within the manufacturing industry. It should be noted that we opted to keep outliers of the markup distribution in our dataset and, therefore, focus on different percentiles of the markup distribution. See Appendix Section D for the change in average markups throughout the period of interest. As evident from Figure 1, markups fall for all percentiles from 2007 to 2016. At the same time, markups have a tendency to rise starting from 2016 for the firms located at the 90th percentile of the markup distribution. While remaining firms could not witness a similar surge, they achieved stabilizing their markups.

Figure 2. Evolution of markups assuming Translog production function

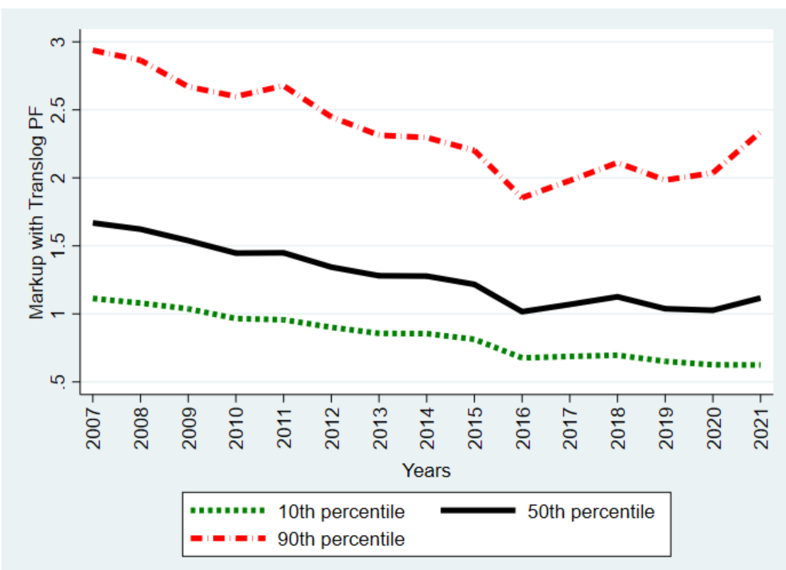
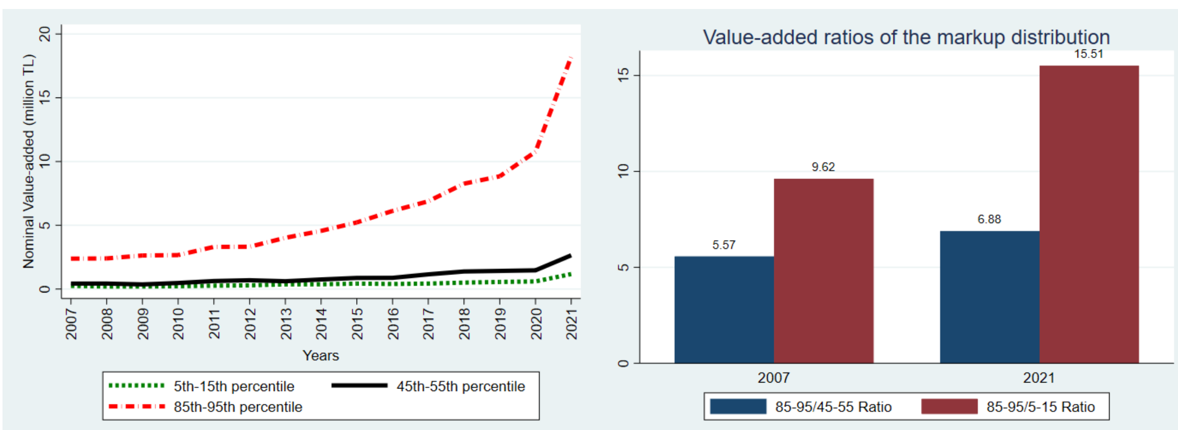


Figure 2 provides one possible reason for the post-2016 developments in profit and labor share: the rise in the markups of the high markup firms. On the other hand, comparing 2021 with 2007 reveals that profit rate increased and labor share decreased despite an overall reduction in markups across the board. As such, the rise in the markups of high-markup firms alone does not account for the general evolution of profit rate and labor share.

To delve into the evolution of market composition, Figure 3's left panel illustrates shifts in average nominal value added across the markup distribution. Evidently, firms with high markups experienced a significant increase in their value-added during the observed period. However, it's important to acknowledge the influence of high inflation, particularly in the post-2016 era, which complicates the interpretation of relative changes in nominal value added across the markup distribution.

To address concerns regarding graph legibility, the right panel of Figure 3 presents a comparison of value-added ratios among different markup distribution percentiles in 2021 versus 2007. It becomes apparent that firms with high markups achieved a notably greater increase in their value added. Specifically, the ratio of the average nominal value added across the 85th-95th percentiles to the 5th-15th percentiles has more than doubled, surging from 6.88 to 15.51.

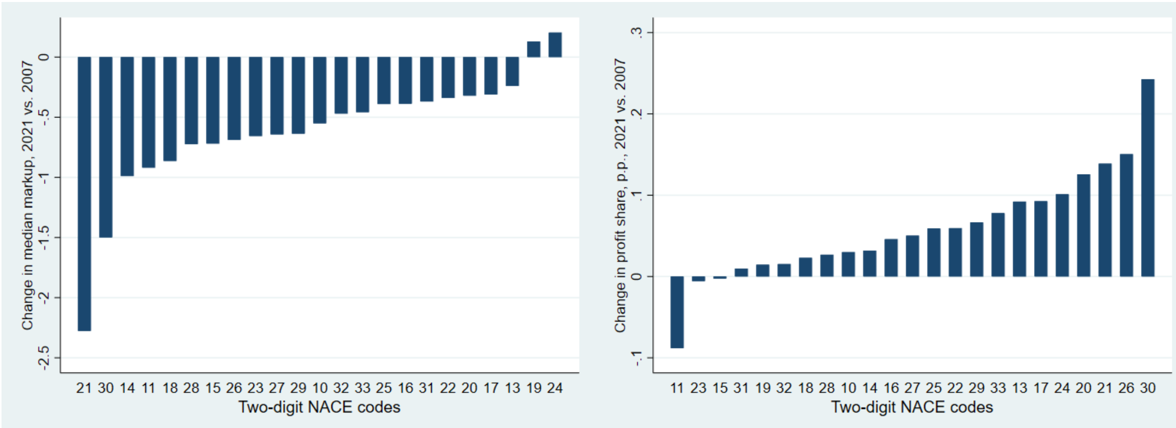
Figure 3. Evolution of value-added across the markup distribution



Notes: The first panel illustrates the evolution of mean nominal value added (in million TL) across the firms in the indicated percentage of the markup distribution. The second panel shows the mean nominal value-added ratios of the exact markup percentiles in 2007 and 2021.

Overall, our descriptive analyses suggest that changing production composition in favor of high markup firms is a prominent feature of the Turkish manufacturing industry over the period of investigation. This compositional change does contribute to the overall rise in profit rate and the decline in labor share. However, there is another factor influencing the pronounced changes in profit rate and labor share, particularly noticeable in the post-2016 period of high inflation. During this time, firms with already higher markups relative to others experience a further markup increase, while other firms, at the very least, manage to stabilize their markups. Coupled with the ongoing change in production composition, the post-2016 years witness a sharp ascent in the overall profit rate along with a drastic decline in labor share.

Figure 4. Changes in markups and profit shares within industries



Notes: Industry definitions are provided in Table 3 of the Appendix. The panels illustrate the changes in the median markup (left panel) and the profit share of total output (right panel) in 2021 relative to 2007.

The distribution of various manufacturing subindustries across the markup spectrum is not necessarily uniform. Consequently, there is a potential concern that our findings might be influenced by a few dominant industries capable of significantly impacting the overall results for manufacturing. To mitigate this concern, we examine the outcomes specific to different manufacturing subindustries.

The left panel and the right panel of Figure 4 respectively show the changes in markups and in profit rates within different industries using two-digit NACE codes. We see that the median markup falls in 2021 compared to 2007 in nearly all industries except (19 and 24, Coke and refined petroleum products, and basic metals) and the profit share increases for the majority of the subindustries with the highest spike in 30 (Other transport equipment) consistent with the results of overall manufacturing industry. Thus, we conclude that the changing market composition in favor of the high markup firms is not specific to a few subindustries but it is a within-subindustry phenomenon. Nonetheless, it is worthwhile to note that the extent of aforementioned developments exhibits remarkable heterogeneity across subindustries as evident from Figure 4.

Appendix Section C presents the evolution of labor shares, profit rates, and markups as in Figure 1 and Figure 2, but for the largest (in terms of market share) four subindustries. Results indicate that manufacturing sector-wide developments persist within subindustries. High markup firms gain momentum both in terms of their markup level as well as their value-added share in the market, fueling the rise in profit rates and the decline in labor shares.

4. Conclusion

This paper investigates the evolution of markups in the Turkish manufacturing industry between 2007 and 2021 using the administrative EIS data from the Republic of Turkiye Ministry of Industry and Technology that provides detailed information on enterprise registers, balance sheets, employee registers, and between-firm sales, among another firm-specific aspects. We utilize the production function approach to estimate firm-level markups. Our findings reveal several key insights:

- In the manufacturing industry of Turkiye, the share of labor in value-added remained relatively unaltered until 2016 but exhibited a dramatic decline thereafter, in the period associated with a high level of inflation. At the same time, the slight increase in the gross profit rate observed until 2016 intensified in this inflationary era.

- The analysis of markup distribution reveals that the upper percentiles of the markup distribution in the Turkish manufacturing industry exhibit a U-shaped trend, decreasing initially and then increasing after 2016. Markups of the remaining firms exhibit an initial decline until 2016, and they are stabilized thereafter.

- Throughout the investigation period, two primary factors underlie the increase in profit rates and the decrease in labor share. Firstly, there is a notable shift in the value-added composition of the manufacturing industry towards high markup firms, which typically feature lower labor shares. Secondly, starting from 2016, high markup firms succeeded in elevating their markups, albeit without fully reaching the levels observed in 2007. This suggests that firm heterogeneity plays a crucial role in understanding the overall trend of markups. Using aggregate measures can mask significant underlying trends and variations.

- The findings underscore that shifts in labor shares, profit rates, and markups are not isolated to a handful of manufacturing subindustries; rather, they are observed across numerous subsectors within the industry.

Monitoring markup trends and understanding the factors driving them can inform policy decisions to promote competition and protect consumer welfare. It is evident from our findings on firm heterogeneity that a one-size-fits-all approach to competition policy may not be effective. The competition policy might benefit from exploration into the underlying factors driving the increase in markups among high markup firms after 2016, along with the changing market composition in favor of high markup firms over the last decade. This approach could facilitate the development of targeted interventions tailored to specific types of firms.

Appendix

A. Data Preparation

We drop firms that do not report balance sheets or employee registers. Firms that remain inactive for at least three consecutive years in the sample period are also excluded. Net sales and capital stock (book values of capital) data are directly observable in the balance sheets. Employee registers in EIS report hours worked and monthly gross salaries for one month of each quarter until 2019 but for every month in 2020 and 2021. We calculate the sum of hours worked and gross wages for every firm and multiply them by four for every year until 2020 to arrive at annual figures for labor costs and total hours worked. Gross salaries are adjusted for severance allowances and social security premiums.

Table 3. Industry definitions and sample sizes

NACE Code	Industry Definition	Sample Size
10	Food products	170.400
11	Beverages	4.421
13	Textiles	107.734
14	Wearing apparel	151.694
15	Leather and related products	35.046
16	Wood and cork, except furniture	41.568
17	Paper and paper products	24.110
18	Printing and reproduction of recorded media	54.794
19	Coke and refined petroleum products	2.031
20	Chemicals and chemical products	40.795
21	Basic pharmaceutical products	3.335
22	Rubber and plastic products	95.230
23	Other non-metallic mineral products	72.170
24	Basic metals	35.468
25	Fabricated metal products, except machinery and equipment	197.699
26	Computer, electronic, and optical products	9.718
27	Electrical equipment	46.947
28	Machinery and equipment n.e.c.	112.093
29	Motor vehicles, trailers and semi-trailers	32.964
30	Other transport equipment	6.460
31	Furniture	94.104
32	Other manufacturing	52.428
33	Repair and installation of machinery and equipment	72.310

Balance sheets incorporate information on accumulated depreciations. Depreciation in each year is recovered by first-differencing this variable. Suppose a firm was inactive in the previous year(s). In that case, the yearly depreciation variable is adjusted accordingly, i.e., by dividing the first-differenced variable by two if a firm was inactive for one year. We replace the flow variables, such as depreciation and net sales, with zero if they are negative. Output is constructed by adding net sales to income from other sources and adjusting for output stock differences. In order to compute the inputs of the firms, we sum the cost of goods sold and other expenditures, adjust for input stock differences, and deduct labor costs and depreciation of capital. Value added can be calculated as the difference between output and input. Gross profit is computed by deducting the labor costs and depreciation from value added.

Table 3 provides the definitions of each manufacturing subindustry along with their total sample sizes across 2007-2021. Note that the tobacco sector (NACE code: 12) is excluded from the analyses due to the low sample size.

B. Production Function Estimation

Following De Loecker and Warzynski (2012), let value-added be produced according to:

$$q_{i,t} = F\left(L_{i,t}, K_{i,t}; \beta\right)\exp(\sigma_{i,t}) \qquad (6)$$

where $\sigma_{i,t}$ represents the productivity known by the managers of the firm but unobserved by the econometrician and β represents a set of coefficients that relate inputs to value-added. The expression in (6) encompasses both Cobb-Douglas and Translog production functions. Remaining explanations and derivations are presented with a Translog value-added production function because it is our preferred specification.

Let $\tilde{q}_{i,t} = lnq_{i,t} + \varepsilon_{i,t}$ where $\varepsilon_{i,t}$ represent an i.i.d. error term unobserved both by the managers and the econometrician. The production function reads:

$$\tilde{q}_{i,t} = \beta_l l_{i,t} + \beta_k k_{i,t} + \beta_{ll} l_{i,t}^2 + \beta_{kk} k_{i,t}^2 + \beta_{lk} l_{i,t} k_{i,t} + \sigma_{i,t} + \varepsilon_{i,t} \qquad (7)$$

with $l_{i,t} = lnL_{i,t}$ and $k_{i,t} = lnK_{i,t}$.

It is a well-known feature that simple OLS regressions of the logarithm of output on the logarithms of factor inputs yield biased estimations of input elasticities due to the simultaneity and selection biases caused by the firm-specific productivity parameter $\sigma_{i,t}$. A vast literature is developed to eliminate these biases. Building on Olley and Pakes (1996), Levinsohn and Petrin (2003) proposes that the level of material inputs, $m_{i,t}$, can be considered as a function of the firm-specific productivity $\sigma_{i,t}$ and the state variable $k_{i,t}$, that is $m_{i,t}\left(k_{i,t}, \sigma_{i,t}\right)$. This idea rests on the assumption that, for any given level of the state variable (decision about whose level is made prior to the realization of the productivity shock), the level of material inputs, which can be adjusted instantaneously, increases in $\sigma_{i,t}$. Thus, inverted $m_{i,t}$ can be used as a proxy for $\sigma_{i,t}$, i.e., $\sigma_{i,t} = {m_{i,t}}^{-1}\left(k_{i,t}, \sigma_{i,t}\right) = d_{i,t}(m_{i,t}, k_{i,t})$.

Ackerberg, Caves and Frazer (2015) points out that, as long as labor input is associated with adjustment costs (e.g., hiring, firing costs), it should be an argument in function $d_{i,t}(.)$, i.e., $\sigma_{i,t} = d_{i,t}(m_{i,t}, k_{i,t}, l_{i,t})$. In the empirical applications, $d_{i,t}(.)$ is usually approximated by a second or a third order polynomial. Plugging $d_{i,t}(.)$ into (7) yields a function of the form:

$$\tilde{q}_{i,t} = \varphi(m_{i,t}, k_{i,t}, l_{i,t}) + \varepsilon_{i,t} \tag{8}$$

where $\varphi(m_{i,t}, k_{i,t}, l_{i,t}) = \beta_l l_{i,t} + \beta_k k_{i,t} + \beta_{ll} l_{i,t}^2 + \beta_{kk} k_{i,t}^2 + \beta_{lk} l_{i,t} k_{i,t} + d_{i,t}(m_{i,t}, k_{i,t}, l_{i,t})$. The first stage estimation yields the estimates of planned output, $\hat{\varphi}_{i,t}$, and the error term, $\varepsilon_{i,t}$. Following the first stage, it is possible to obtain the firm-specific productivity shocks for any β via: $\hat{\sigma}_{i,t} = \hat{\varphi}_{i,t} - \beta_l l_{i,t} + \beta_k k_{i,t} + \beta_{ll} l_{i,t}^2 + \beta_{kk} k_{i,t}^2 + \beta_{lk} l_{i,t} k_{i,t}$.

The estimates of coefficients β can be searched for in a second stage assuming a Markov chain process for the firm-specific productivity shock, $\sigma_{i,t} = g(\sigma_{i,t-1}) + \xi_{i,t}$, utilizing a set of moment conditions, $E(\xi_{i,t} x) = 0$ where $x \in \{l_{i,t-1}, k_{i,t}, l_{i,t-1}^2, k_{i,t}^2, l_{i,t-1 k_{i,t}}\}$ and by employing standard GMM techniques. In a next step, firm-specific labor and capital elasticities can be calculated as:

$$\delta_{i,t}^{q,L} = \hat{\beta}_l + 2\hat{\beta}_{ll} l_{i,t} + \hat{\beta}_{lk} k_{i,t}, \tag{9}$$

$$\delta_{i,t}^{q,K} = \hat{\beta}_k + 2\hat{\beta}_{kk} k_{i,t} + \hat{\beta}_{lk} l_{i,t}. \tag{10}$$

It should be noted that this study utilizes the "prodest" command developed in Rovigatti and Mollisi (2018). In particular, we run the "prodest" command with 30 repetitions, a tolerance level of 10^{-6} and the Nelder-Mead optimizer. A well-known feature of Levinsohn and Petrin (2003) algorithm and Ackerberg, Caves and Frazer (2015) correction is that the results of the second stage optimization may be sensitive to initial values, especially under low sample sizes (see Rovigatti and Mollisi (2018)). While our sample sizes are generally sufficiently large, we nevertheless estimate the production functions of each manufacturing sub-industry with five different seeds and average the resulting coefficients.

As standard in the literature of production estimation, we utilize the deflated monetary values of value-added, capital stock, and material inputs since quantities are not available. In particular, we deflate value-added by producer price indices (PPI) of three-digit NACE industries taken from the Turkish Statistical Institute (TUIK) whenever possible. If the producer prices of a three-digit industry are unavailable, we utilize two-digit NACE industry PPI, letter NACE industry PPI, or general PPI in this order, depending on availability. Our capital input is the book value of capital deflated with the capital goods price index provided by TUIK.

EIS allows us to observe between firm sales. Thus, we construct firm-specific material input price indices based on the composition of inputs from different three-digit NACE industries. Once again, we use lower-digit price indices of an industry if producer prices are not available at the three-digit level. EIS also allows us to observe imported inputs. For the imported inputs, we construct a specific price index by multiplying the EUR/TRY exchange rate with the PPI of the EU. Finally, total hours worked are employed as the labor input into the production function. It should be noted that while utilizing deflated monetary values may lead to well-known biases in the estimation results, it is shown that there is a high correlation between biased and true markup estimates (De Ridder et al., 2022). Therefore, trends over time and across industries can be conveniently investigated.

Finally, the total monetary value of value-added observed in the dataset is $\tilde{q}_{i,t} = lnq_{i,t} + \varepsilon_{i,t}$, that is, it includes the idiosyncratic error term $\varepsilon_{i,t}$. Utilizing the error term estimated in the first-stage of the production function estimation, we convert realized value-added into planned value-added. Specifically, our final markup estimates read:

$$\mu_{i,t} = \delta_{i,t}^{q,L} \frac{P_{i,t}\, \tilde{q}_{i,t}(\sigma_{i,t}, L_{i,t}, K_{i,t})/\exp(\varepsilon_{i,t})}{w_{i,t} L_{i,t}}. \tag{11}$$

C. Results with Cobb-Douglas Production Function

Table 4 and Figure 5 report the equivalents Table 1 and Figure 2 when the underlying production function is assumed Cobb-Douglas instead of Translog. The estimation of Cobb-Douglas production function virtually follows the same steps mentioned in the previous section with the exception that equation (7) is replaced by:

$$\tilde{q}_{i,t} = \beta_l l_{i,t} + \beta_k k_{i,t} + \varepsilon_{i,t} \tag{12}$$

Equations (9) and (10) also become redundant since coefficients β_l and β_k directly imply labor and capital elasticities. In this case, elasticities do not differ across firms as opposed to the elasticities that result from the estimation of a Translog production function.

The average labor elasticity, which is the crucial component of markup calculation, is similar to that of Translog production function estimation. Similarly, trends across the markup distribution are very similar in comparison to the markup estimations with the Translog production function.

Figure 5. Evolution of markups assuming Cobb-Douglas production function

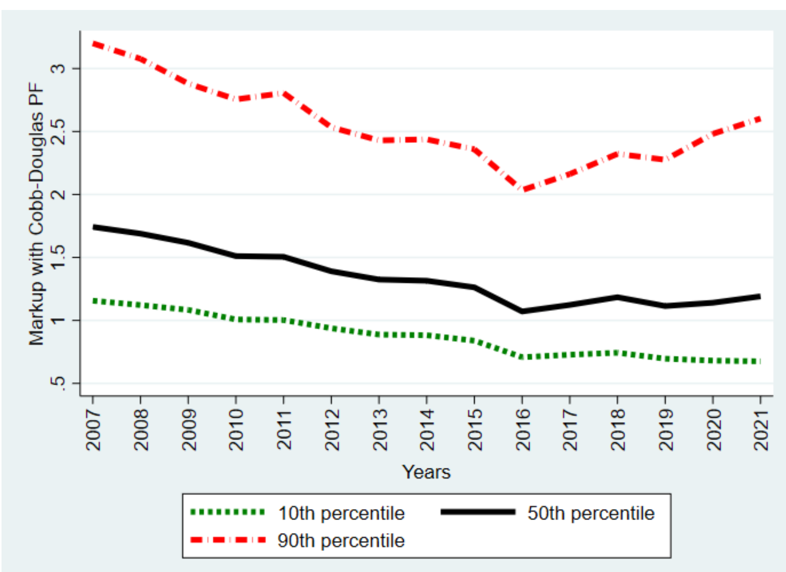


Table 4. Cobb-Douglas production function estimation results

NACE Code	Market Share	Labor Elasticity	Capital Elasticity	Returns-to-scale
Avg.	-	*0.854*	*0.037*	*0.891*
10	0.142	0.856	0.051	0.907
24	0.120	0.852	0.023	0.875
29	0.091	1.000	0.030	1.030
13	0.085	0.831	0.056	0.887
25	0.059	0.811	0.055	0.866
20	0.056	0.876	-0.029	0.847
27	0.056	0.945	0.022	0.966
22	0.054	0.852	0.030	0.882
14	0.054	0.832	0.054	0.886
28	0.049	0.844	0.033	0.877
23	0.048	0.807	0.042	0.849
19	0.043	0.886	0.120	1.005
17	0.027	0.864	0.000	0.863
31	0.018	0.833	0.066	0.899
26	0.014	0.907	0.042	0.949
32	0.014	0.808	0.054	0.862
16	0.013	0.802	0.063	0.865
21	0.013	0.894	-0.079	0.814
33	0.012	0.755	0.044	0.799
30	0.011	0.784	0.068	0.852
15	0.008	0.816	0.074	0.890
11	0.007	1.010	0.025	1.035
18	0.007	0.770	0.017	0.787

Notes: Sectors are ranked based on their market share within the manufacturing industry. Sector definitions can be found in the Table 3 of the Appendix. The first row presents the average elasticities and returns-to-scale across manufacturing industries.

D. Further results

Figure 6 presents the changes in simple average markups and average markups weighted with firms' market shares. Weighted average markups appear relatively high. This is because we opted not to drop the outliers. Thus, the main text focuses on the evolution of markups at the specific markup percentiles. Nonetheless, the U-shaped trend of weighted average markups is consistent with the narrative in the main text, i.e., firm composition shifts in favor of high markup firms over the sample period and, simultaneously, high markup firms achieve an increase in their markups as of 2016.

Figure 7, Figure 8, and Figure 9 figures, respectively, demonstrate the evolution of labor shares, profit shares, and markups of the largest four industries, which, in total, constitute approximately 45% of the manufacturing industry market.

Figure 6. Evolution of average markups assuming Translog production function

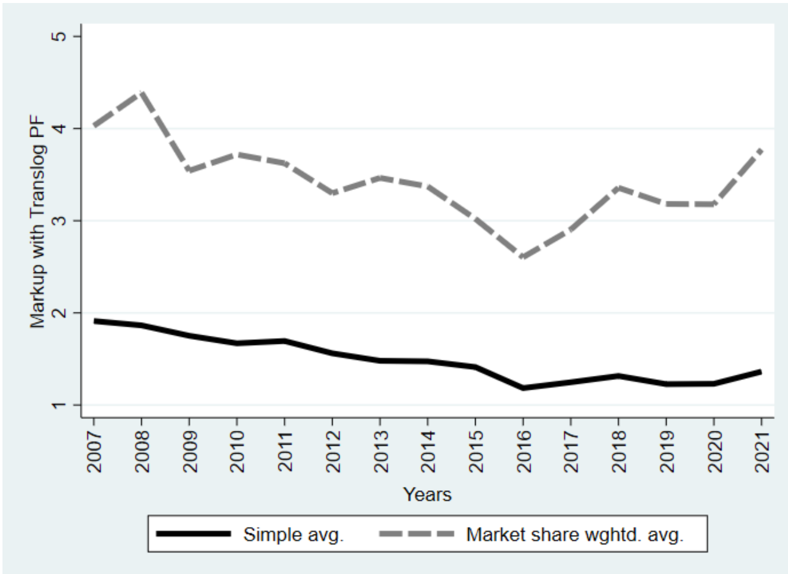


Figure 7. Labor shares of the largest four industries

Figure 8. Profit shares of the largest four industries

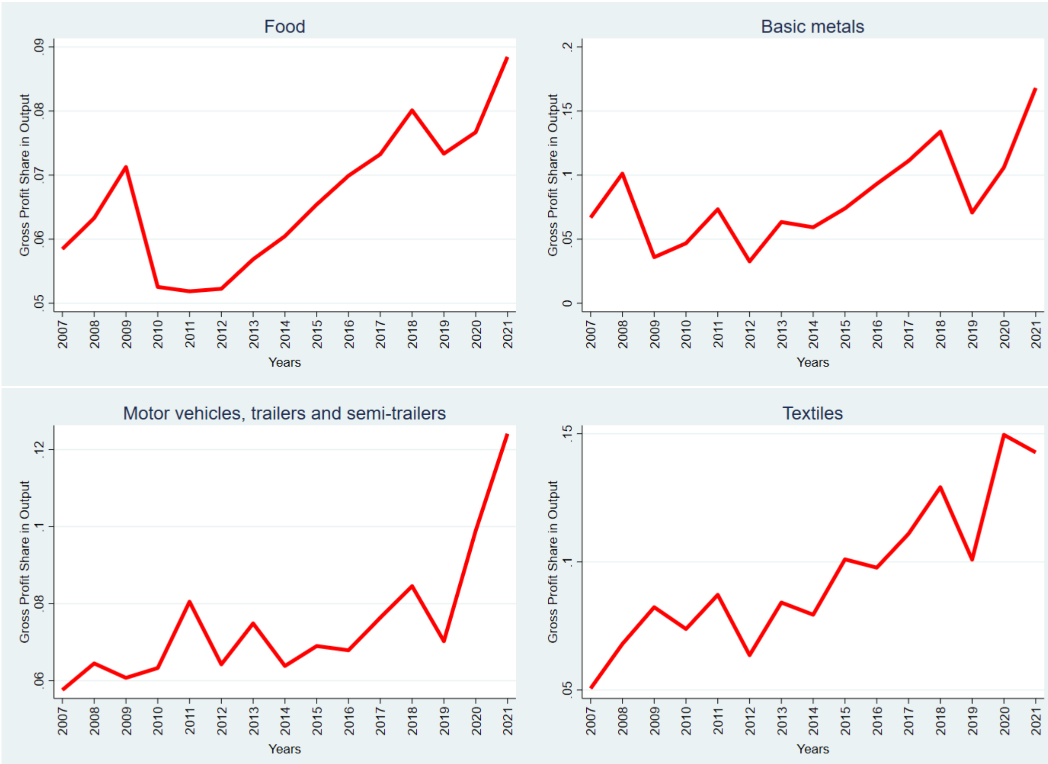
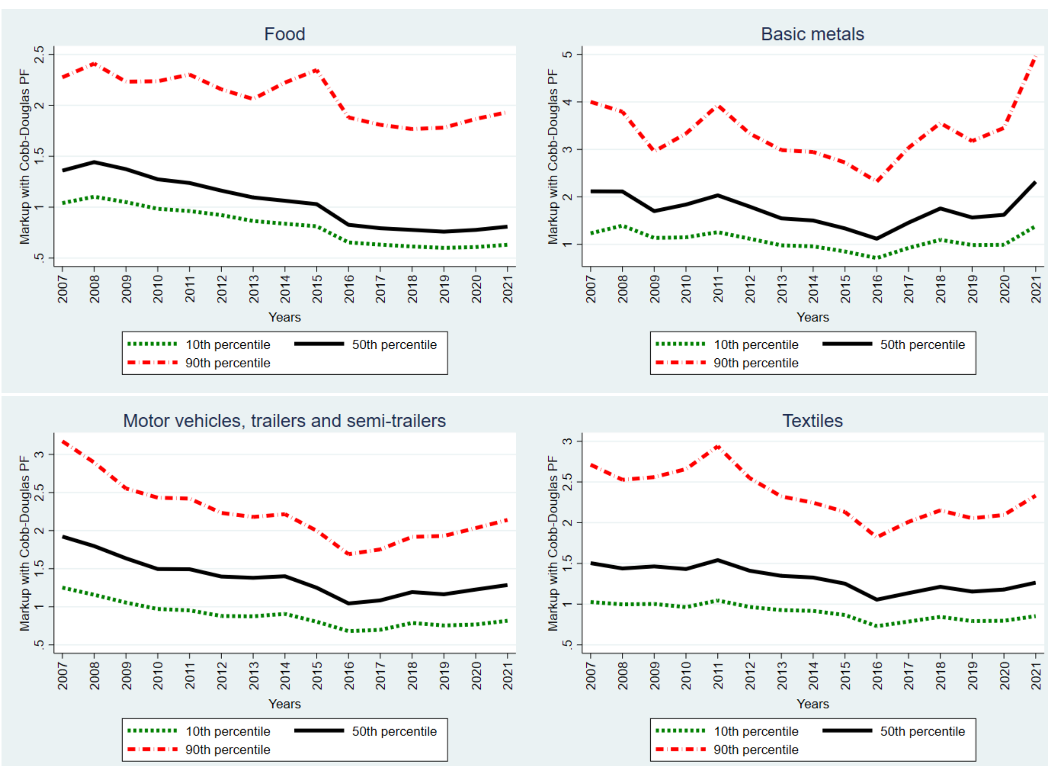


Figure 9. Markups of the largest four industries



Declarations

Ethical approval. Not applicable.

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