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MEASURING MARKET POWER:
MACRO AND MICRO EVIDENCE FROM ITALY

by Emanuela Ciapanna[a], Sara Formai[b], Andrea Linarello[b] and Gabriele Rovigatti[a]

Abstract

In this paper, we provide an assessment of the evolution of markups in Italy in the last twenty years. To achieve this, we resort to both macro and micro data and estimation techniques, namely reduced-form accounting measures (price-cost margins) and production function model-based indicators. When using aggregate data, we adopt a comparative approach and analyse markups in the four main Euro area countries, whereas the micro-level analysis focuses on Italy. According to our findings i) markups show flat/slightly decreasing dynamics across EU countries, settling to a 1.1 level on average; ii) the aggregate dynamics hide substantial cross-sector and cross-firm heterogeneity; iii) the within-firm component is the most relevant driver of markup dynamics; iv) no top firms-driven dynamics emerge. Our results differ from those obtained by De Loecker and Eeckhout (2018) for two main reasons: first, our sample is more representative of the Italian corporate sectors as it includes non-listed firms; second, rather than assuming common technology across countries, we estimate country-specific technology parameters. Finally, we propose an encompassing measure of market power, summarizing the previously investigated indices in a principal component framework and we confirm its effectiveness based on a set of validation variables.

JEL Classification: D2, D4, E2, L1, O3.
Keywords: markups, competition measures, Euro Area, micro-macro data.
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Contents

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Introduction[1]

The degree of competition influences several economic outcomes: consumers' welfare, productivity, international competitiveness, innovation and business dynamism, and ultimately economic growth. However, over the past two decades, there have been signs that competition has weakened across several industries in the United States, as a result of the emergence of a few superstar firms exerting more market power than before. In particular, an intense public debate has arisen regarding the increase of market power amid corporate giants in the tech industry (e.g. the so called GAFAM), whose ambiguous role of "monopolistic innovators" falls more and more often under the lenses of Antitrust Authorities. These firms were typically more dynamic than others, tentatively suggesting that changes in the structure of product markets—such as the winner-takes-most dynamics benefiting the most productive and innovative firms, rooted in part in specific intangible assets— are behind at least some of the overall rise in market power.

The heated policy debate has revived the interest for analysing market power dynamics, leading to several contribution in the empirical microeconomics literature, though mostly focused on the US case. The evidence for European countries is still scant, apart from two notable exceptions, which achieve opposite conclusions. On the one hand, De Loecker and Eeckhout (2018), in their study on global market power, confirm for Europe the same findings they had retrieved for the US: "[...] European countries all show an increase in markups that is in line with the overall trend", with the steepest dynamics recorded in Denmark, Switzerland and Italy. On the other hand, Gutiérrez and Philippon (2019) do not find any rising concentration and profits in major EU countries.

The present paper aims at shedding further light in this debate, providing an assessment of the evolution of markups in Italy in the last decades, based on both macro and micro data and on different measures and estimation techniques, which we interpret in a comparative perspective. When using aggregate data, we compare the Italian trends with those of the other main euro area countries -namely France, Germany and Spain. The analysis based on micro data benefits of a unique integrated firm-level dataset sourced from Istat, covering the universe of Italian firms.

Our findings depict a different pattern of market power in the four largest EU economies compared to the United States. First, we do not retrieve an increasing trend: markups computed from macro data show either flat or slightly decreasing dynamics, settling on average in level at 1.1 in Italy, France and Germany and at 1.2 in Spain (against 1.6 in the United States). Second, differently from the US, no top firms-driven trends emerge: though larger and more innovative firms show higher markups on average, the dynamics is flat also in the top percentiles. Third, our data show relevant heterogeneity across sectors in markups patterns. Nevertheless, changes in aggregated markups are driven by adjustments within the single sectors, rather that variations in the average weight of the sectors themselves. These findings underline the relevance of micro data in studying markups dynamics. Focusing on Italy, we then employ data for the universe of firms and confirm a scenario characterized by rather stable markups over the last 10-15 years. Markups based on the Lerner index are higher -on average- in services than

[1]The present paper is part of the project "Changes in the Italian productive system", which is a collaboration between the Bank of Italy and the Italian National Statistical Agency (Istat). We are grateful to Istat for letting us access the data on the universe of Italian firms, especially to Roberto Monducci, Stefano Costa and Stefano De Santis. All computations on these data, described in the paper, were carried out on-site at Istat premises in accordance with Italian confidentiality laws. We are also indbted to Matteo Bugamelli and Roberto Torrini, Federico Cingano, Florian Ederer, and participants to the Bank of Italy internal seminars. The views expressed in the article are those of the authors and do not involve the responsibility of the Bank of Italy.

in manufacturing, where the tradable nature of the products plays a pivotal role. Among services, those showing higher figures are Professional and Information and Communication sectors, while retail trade displays quite low values and a flatter evolution over the considered time horizon.[2] Moreover, our decomposition analysis shows that the within-firm component is the most relevant in explaining markups evolution over time, whereas the reallocation one, which represents the driving force in the United States, appears to be second order. Our main findings do not change when we restrict the analysis to the smaller sample of incorporated firms, which allows us to estimate markups following the production function-based methodology (see De Loecker, Eeckhout and Unger, 2020). We compare our results to those in De Loecker and Eeckhout (2018). In particular, we start from replicating their analysis with their dataset and assumptions. Then, we show that the differences with our results are ascribed to two restrictive hypotheses: their highly selected sample (limited solely to listed companies) and the assumption of common elasticity across different countries. We discuss the implications sourcing from these restrictions and show how, once these are relaxed, our results hold valid.

Finally, we implement a principal component analysis on the different markup measures previously considered, and propose the first component as a composite measure of market power. We test its effectiveness on a set of plausible validation variables, i.e. concentration indices, total factor productivity and churn rate. We retrieve the expected sign and magnitude in the correlation coefficients with all the proposed indicators.

Our work is related to many contributions in the recent literature on market power, although it represents one of the few studies focusing on European countries. For the US, Stiglitz (2015) and Eggertsson, Robbins and Wold (2018) argue that several puzzling trends, such as decreasing labor and investment shares and increasing market concentration, could be explained by rising market power and profits. Their findings are confirmed by De Loecker, Eeckhout and Unger (2020) (DLEU, henceforth), who show that in the US firm markups rise from 18% to 67% between the 1970s and 2016, and by Hall (2018), who finds more modest increases. Gutiérrez and Philippon (2017) also provide evidence of rising concentration and margins; Caballero, Farhi and Gourinchas (2017) ascribe the puzzling relation between the fall in real interest rates and the flat evolution of ROE emerging throughout the last decade to a rise in capital risk premium, an increase in monopoly rents from markups, accompanied by a capital-biased technical change.

Regarding other economies, and in particular EU countries, there is no clear-cut empirical evidence for markups evolution. The very recent contribution of De Loecker and Eeckhout (2018) on global market power, building on DLEU results and methodology, extends the analysis as to include 134 countries, starting in 1980. They document a steady rise of global markups from around 1.17 in 1980 to about 1.6 in 2016. In Europe, the increase was around 60%, to above 1.6 in 2016. As for Italy, they find a rather high level of markups and one of the sharpest increase since the 1980s, concentrated in the first and last years of the sample. Using Orbis data on firms with more than 20 employees for 26 OECD countries, Calligaris, Criscuolo and Marcolin (2018*a*) find that in the period 2001-2014 average markups are increasing over time (around 6%) and that these trends are mainly driven by a steep increase in the

[2]Due to data availability, our micro-level analyses are conducted for a time period ranging between 2004 and 2018. This is a plausible explanation for the almost constant trend we retrieve for the retail trade sector, which underwent a major liberalization reform in the end of the nineties (Decreto legislativo n. 114/1998, known as "Bersani Law"). The reform aimed to increase competition and foster the modernisation of the Italian retail sector by reducing entry barriers and administrative burden.

top decile of the distribution. However, recent contributions (see for instance Traina, 2018 and Raval, 2020) have shown that DLEU's findings are sensitive to measurement and estimation choices, while our results appear to be consistent across the different proposed methodologies and to provide a coherent picture.

More in line with our analysis, Gutiérrez and Philippon (2019) do not find any rising concentration and profits in major EU countries. According to their model, the US/EU differences are driven by a stronger and more independent Competition Authority in the European context. Very recently, on the other hand, Koltay, Lorincz and Valletti (2021) use a different approach and a new dataset on major EU countries and UK (1998 to 2019) to find an increased pace toward market concentration and the creation of oligopolies in several industries. The difference in the data aggregation level, as well as in a number of methodological choices, makes the comparison of results a very hard task, at best. In a recent ECB working paper, McAdam et al. (2019) propose a macro analysis in a comparative perspective. Their findings show that markups have been slightly declining in the Euro area in the last decades. As of single country studies, Gradzewicz, Mućk et al. (2019) document declining markups in Poland, which the authors relate to the increasing globalization and the opening of the market to foreign firms; Loecker, Fuss and Biesebroeck (2018) for the period 1980-2016 estimate markups for the universe of Belgian firms that compulsory submit annual accounts and find that the aggregate markups increased during the first fifteen years of around 15% while it remained relatively stable in the remaining years. According to De Loecker and Eeckhout (2018), Belgian markups almost doubled over the same period.

Apart from the rekindled interest in the recent economic literature for the study of the evolution of market power as an explanatory variable of some long-term trends, the analysis of competitive dynamics has a long tradition, with outstanding theoretical and empirical contributions, both in the macro and in the microeconomics field. Syverson (2019) proposes a review of the literature on market power, pointing out the flaws of the various methods, from a number of different perspectives. First, he discusses theoretical measures of market power in comparative terms, shedding light on the relationship between the accounting approach, which abstracts from scale elasticity and the concentration measures. Then he discusses how a prominent strand of macro market power research has used accounting data to estimate markups and points out seeming inconsistencies among the empirical estimates of these values in the literature. Successively, he focuses on the more recent contributions, linking a rise in market power to lower levels of investment and a lower labor share of income. Throughout his review, he characterizes the congruence and inconsistencies between macro evidence and micro views of market power and, when they do not perfectly overlap, explain the open questions that would need to be answered to make the connection complete. Among these, one issue that we deal extensively with in our work is the role of sectoral and firms' heterogeneity, which appears to be a very relevant determinant in markups development. In fact, both using multi-country sector-level data and restricting the analysis to one-country firm-level observations, we retrieve that the most important driver of markup evolution in the EU countries under consideration is the within sector/within firm component, pointing out the difficulty of posing the matter in aggregate terms.

The rest of the article is organised as follows. Section 2 describes global stylized facts and macroeconomic puzzles, comparing the US and the main EU countries; Section 3 proposes the macro-level analysis with cross-country comparisons; Section 4 focuses on the Italian case and presents our micro-level evidence based on two different datasets (ASIA-Frame and Cerved) and measures. Section 5 discusses our results, comparing them to the main contribution for Italy in the recent literature. Our proposed synthetic measure is discussed in Section 6, while Section 7 concludes. Further descriptive evidence as well as technical details on the theoretical foundation of markup measures are relegated to the Appendices.

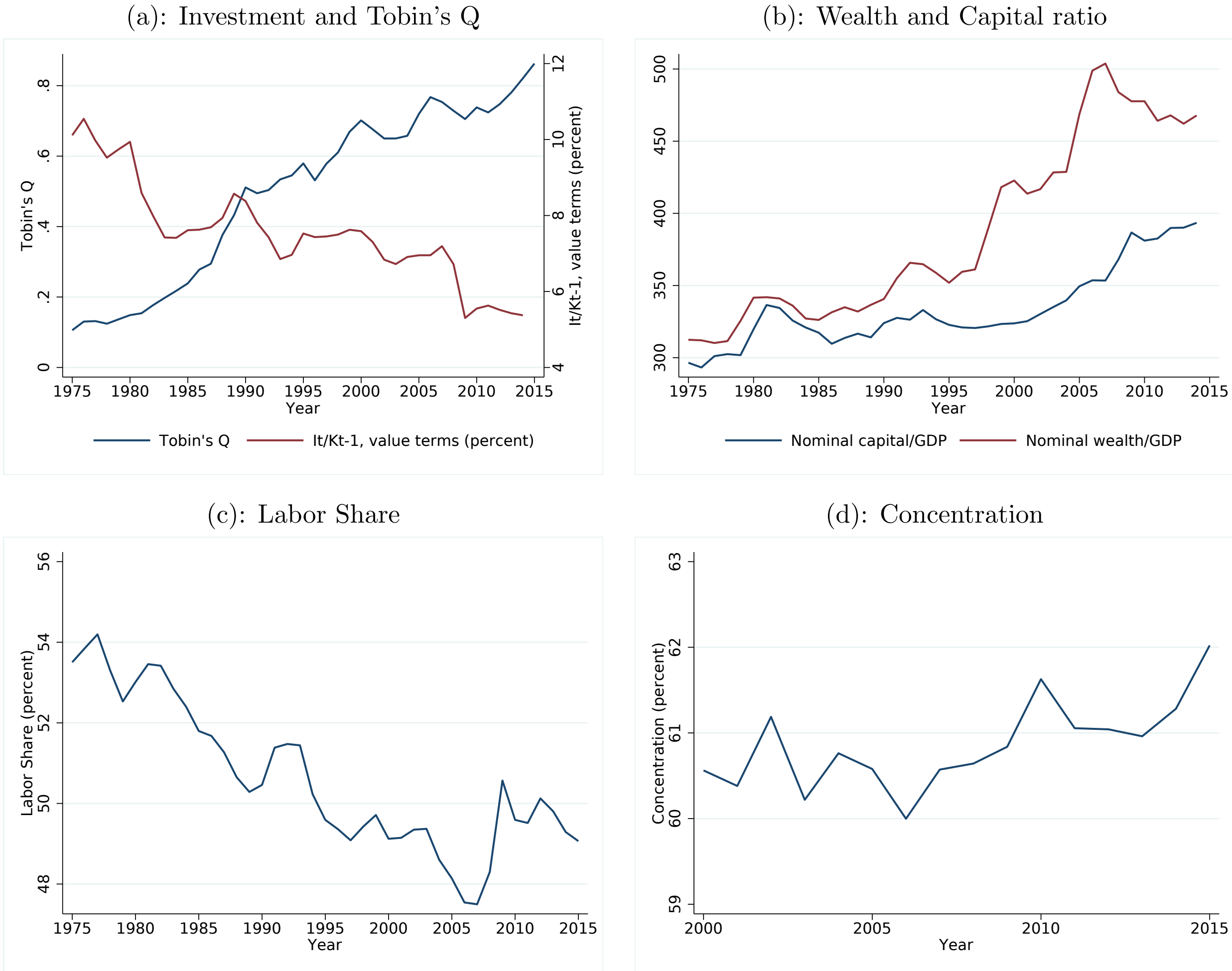
2 Global and EU Stylized Facts

Competition is the foundation of the market economy. It leads to lower prices, higher quality products and more attractive wages. When firms compete for market shares, productivity increases, more varieties of goods arise at lower prices, boosting economic growth and welfare. However, over the past two decades, there have been signs that competition has weakened across several US industries, as a few "superstar" firms have been increasingly exerting market power. For instance, in the early 2000s, the top two Telecommunication service providers accounted for around 30% of industry sales; as of today, they control around 70%. In the US airline industry, the top four airlines have increased their share of domestic air travel from 48% to 68% within the last twenty years. In the aggregate, all indicators point to rising concentration for more than 3/4 of US industries, with the largest increases occurring in information and communication technology (IT) and retail trade.

However, higher concentration is not a strong indicator for lack in competition, particularly when superstar firms arise, as a result of a winner-take-the-most phase, as it is for the GAFAM. Other measures of rising market power have then been proposed and analysed in the literature to further investigate the state of competition in advanced countries.[3] Most of them point to an increasing evolutionary trend of market power -particularly in the United States and in the most advanced countries- which is often indicated as a possible explanation for several macroenomic conundra that have been emerging over time (De Loecker, Eeckhout and Unger, 2020). In figure 1 we report the most impressive ones referred to roughly the last 40 years: (a) the sluggish investment rates, despite the fall in borrowing costs and an increasingly higher Tobin's Q; (b) a widening gap between financial and productive wealth - which is proxied by the ratio of nominal wealth and capital over GDP; (c) the steady decrease in the labor share; and (d) increasing concentration. A marked raise in firms' markups (as well as in profitability) may rationalize a few of the above facts within a classical production framework, and solve at least partially some inconsistencies, such as the "missing" investments while the Tobin's Q increases.

[3]Some interesting results are summarized in IMF (2019).

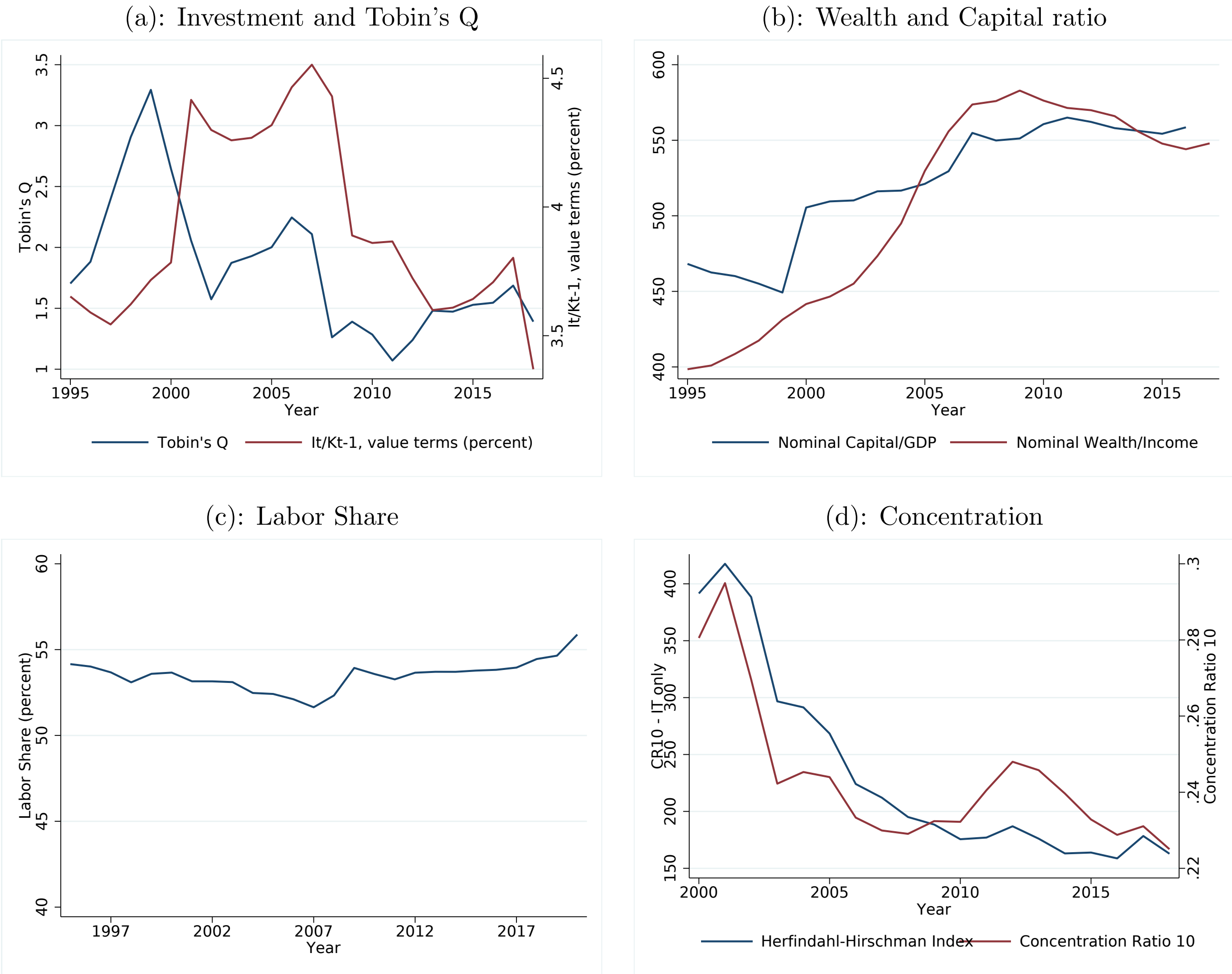
Figure 1: Trends in advanced economies - 1975/2015 (IMF, WEO, April 2019).



Notes: (a) Tobin's Q and investment ratio ($\frac{I_t}{K_{t-1}}$); (b) financial wealth ($\frac{Wealth_t}{GDP_t}$) and productive wealth ($\frac{K_t}{GDP_t}$); (c) labor share ($\frac{W_t}{Y_t}$); (d) concentration dynamics. All measures refer to the average value among advanced economies in the 1975/2015 period as reported by the IMF in its *World Economic Outlook*, 2019.

Nevertheless, when focusing on the EU, most of the previously described conundra seem to vanish. In figure 2, we report the corresponding series presented in figure 1 for Italy, Germany, France and Spain. In panel (a), we show that the investment rate decreases correlate with the Tobin's Q series over the last decades; in panel b) the widening of the wealth/capital ratio started only in the early 2000's; finally, in panel c) the labor share shows a flat/slightly increasing evolution, and its level is well above the average global value - ≈ 56% v.s. 49%; consistently, in panel d) both concentration indices have been decreasing. Thus, the picture emerging from a first look at macroeconomic trends in the major EU economies seems to point to a less pronounced lack of competition problem compared to the US. In the following sections, we further investigate whether this intuition is confirmed, taking the analysis at a higher level of detail and enriching our tools to measuring market power.

Figure 2: Trends in EU benchmark countries (National Accounts, Eurostat).



Notes. (a) Tobin's Q and investment ratio ($\frac{I_t}{K_{t-1}}$); (b) financial ($\frac{Wealth_t}{GDP_t}$) and productive wealth ($\frac{K_t}{GDP_t}$); (c) labor share ($\frac{W_t}{Y_t}$); (d) concentration dynamics (CR10 and HHI). (a), (b), (c): all measures refer to the GDP-weighted average value in Italy, Germany, Spain and France between 1995 and 2015. (d): Italy only. Source: National Accounts, Eurostat and CADS, CERVED Group.

3 Macro Evidence

In this section, based on sector-level data, we document the evolution of markups in the four main EU countries over a time range between 1995 and 2018. We resort to two different measures in a comparative setting: the first relies on a transformation of the Lerner index, computed on National accounts data, the second is based on the Hall-Roeger production function estimation model. We further analyse the drivers of markups evolution by looking at within and between sectors dynamics separately to shed some lights on the main sources of heterogeneity. In the following subsection, we describe the data and methods employed, while we refer to the next one to present our results of the decomposition analysis.

3.1 Data and definitions

In order to study markups evolution across countries, we employ the National Accounts data provided by Eurostat, from 1995 to 2018. In particular, for each (one digit) NACE Rev. 2 sector we gather data on gross ouput, value added, capital formation, total compensation costs, intermediate input costs, total number of workers and employees. The main aggregate for the analysis, *BASE*, includes both Industry and Market Services (sectors C to N), while excluding Financial Services and Real Estate (sectors K and L).[4]

We complement National Accounts with the AMECO database, provided by the European Commission's Directorate General for Economic and Financial Affairs. It features data on several EU and EU-candidate countries, the euro zone and several OECD countries. In particular, we use the data relative to the long-term interest rate deflator as a proxy for cost of capital.

The Lerner markup Our baseline measure for markups derives from a simple accounting measure, the Lerner markup, which can be retrieved from a oligopoly competition problem á la Cournot in an industry with N heterogeneous firms. The main advantage of the Lerner markup is that it does not suffer from estimation and measurement errors. We use a slightly modified definition of the price-cost margin measure (the Lerner Index, $Lerner_{st}$), computed, for sector s ans year t, as the ratio between the Gross Operating Margin (GOM) and total output.[5]

$$\mu_{st}^{Lerner} = \frac{1}{(1 - Lerner_{st})}$$

μ_{st}^{Lerner} has the further advantage that can be computed both at the industry- and at the firm- level, easing the comparison across macro and micro measures of markups. A similar accounting approach to markup measurement, even though in different contexts, has been recently employed by Antras, Fort and Tintelnot (2017) and Autor et al. (2020).

The Hall/Roeger framework The second measure of markup we employ in our analysis was proposed by Hall (1988) and refined by Roeger (1995), and it builds on a somewhat different framework. More specifically, following the intuition by Solow (1957), they realized how the Solow Residuals (SR) would not nail down the technological changes (θ) in case of imperfect competition, but rather a weighted sum of θ and the growth rate of the output/capital ratio. In turn, the weights are a monotone transformation of the markups.[6] Hence, Roeger proposed to sum up the quantity-based SR, and their dual problem counterparts (the price-based SR, or SRP) to "net out" the unobservable technological changes and estimate the markups on simple observable (i.e., accounting) measures. More specifically, for each

[4] The exclusion of the real estate sector, which constitutes a clear outlier in terms of markup, is common in the extant literature - see e.g. Christopoulou and Vermeulen (2012) and Calligaris, Criscuolo and Marcolin (2018*b*).

[5] See appendix C for a full-fledged description of both the derivation and the empirical approximation of the variables that we employ.

[6] Refer to appendix C for the full description of the underlying models.

sector s, the estimating equation reads

$$\underbrace{(\Delta p_t + \Delta Q_t)}_{Output\, growth} - \alpha_{N_t} \underbrace{(\Delta w_t + \Delta N_t)}_{labour\, cost\, growth} - \alpha_{M_t} \underbrace{(\Delta m_t + \Delta M_t)}_{Input\, cost\, growth} - (1 - \alpha_{N_t} - \alpha_{M_t}) \underbrace{(\Delta r_t + \Delta K_t)}_{Capital\, cost\, growth} =$$
$$\underbrace{SR_t - SRP_t}_{y_t} = \underbrace{\left(1 - \frac{1}{\mu_t^{Roeger}}\right)}_{\beta} \underbrace{[(\Delta p_t + \Delta Q_t) - (\Delta r_t + \Delta Kt)]}_{x_t} \tag{1}$$

where, for estimation purposes, μ_{st} is constant and the relative estimating equation reads $y_t = \beta x_t + \epsilon_t$. The linear regression of y_t on x_t yields a consistent estimate of β_s - which can be inverted to obtain the (time invariant)

$$\hat{\mu}_s^{Roeger} = \frac{1}{1 - \hat{\beta}}$$

Accounting for self-employment: *per hour* correction In the national accounts data, $GOM_{st} = ValueAdded_{st} - LaborCost_{st}$, where $LaborCost_{st}$ stands for total compensation of employees only - i.e., compensation of self-employed is not accounted for, and adds up to the profits' share. Such a measurement may lead to severe bias in the economic interpretation of the data, as both the aggregate markups and the profits' share (and, as a complement, the labor share) do not account for the contribution of self-employed to the creation of value added. On top of that, the amount of bias critically depends on the sector, as some feature a larger presence of self-employed - e.g., professional sectors - whereas in other cases their share is negligible - e.g., administrative. In order to tackle this issue, we implement a correction which exploits the availability in the national accounts data of the number of self-employed workers, the number of hours they have worked, and their relative weight at the sector level. More specifically, we define the "corrected" Lerner index by imputing the average cost per hour to the total hours worked by self-employed individuals ($\frac{LaborCost_{st}}{hours_{st}^{emp}} \times hours_{st}^{self}$)

- *per hour*-corrected index: $\widetilde{LaborCost}_{st}^{H} = LaborCost_{st}(1 + \frac{hours_{st}^{self}}{hours_{st}^{empl}})$

Throughout the paper, we use $\widetilde{LaborCost}_{st}^{H}$ as baseline measure.[7]

Variable aggregation For all samples, we build the measure of aggregated Lerner markups as the value added-weighted average across sectors. More specifically, for each time t we define

$$\mu_{st}^{Lerner} = \frac{\sum_{s=1}^{S} \mu_{st}^{Lerner} \times VA_{st}}{\sum_{s=1}^{S} VA_{st}}$$

where $s \in [1, .., S]$ stands for the NACE Rev. 2 sectors, and VA_{st} is the yearly sectoral value added, as reported in the National Accounts.

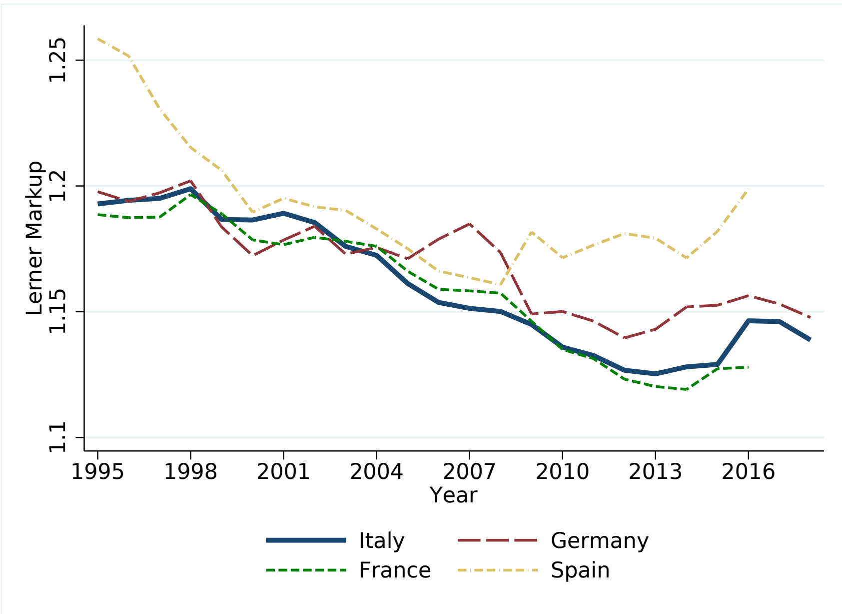
[7]The *per hour* correction involves two different corrections, as one needs to know both the share of self-employees and the number of hours that they have worked to implement it. A simpler correction - yet more prone to the measurement issue outlined above - only requires adjusting $LaborCost_{st}$ with the *number* of self-employees, hence focusing on the extensive rather than the intensive margin. More specifically, it is possible to compute the average sector-level wage of employees, and impute it to the self-employed workers (in formulas, $\widetilde{LaborCost}_{st}^{P} = LaborCost_{st}(1 + \frac{self}{employees})$). Typically, however, $\widetilde{LaborCost}_{st}^{H} > \widetilde{LaborCost}_{st}^{P}$ since $\frac{hours^{self}}{hours^{emp}} > \frac{self}{employees}$ because self-employees work, on average, longer hours. Results obtained with the *per person* correction are available upon requests.

Descriptive Statistics In table 1 we report the main statistics (mean, standard deviation, median) of the variables. The unit of observation is a country/sector/year tuple. All averages are value added-weighted and we also further distinguish between the full sample (columns 1-3) and the 2006-2018 period (columns 4-6, including a complete decade and extended as to contain a full year before the Great Recession). In terms of Gross Output, Value Added, Labor Cost and Capital, Germany shows the highest values across sectors in both periods considered; however, there is great variation across economic activities - as confirmed by the very high standard deviation value and by the remarkable distance between the weighted mean and the median values, also confirmed by the (unreported) high skewness.

3.2 Cross-country comparison and sector-level heterogeneity

In figure 3 we report the dynamics of markups in Italy alongside Germany, France and Spain. The figure highlights two crucial facts. First, the average level of markups for the period 1995-2018 in the main EU countries is between 1.1 and 1.2, and it is lower than in the US as reported by De Loecker, Eeckhout and Unger (2020). Second, the dynamics of the markup is slightly decreasing in all countries until the Great Recession, then waves upward for Spain and flattens for Germany, whereas in Italy it inverts the trend only in 2014 - and to a rather small extent. Overall, the dynamics of markups in Italy does not differ from that of the other main European countries, and it shows a very low level of variation throughout the period.

Figure 3: Country-level markups



Notes: average μ^{Lerner} dynamics in Italy (solid blue line), Germany (dashed red), France (dotted green) and Spain (dotted yellow), 1995-2018. The sample includes all Industry and Market Services NACE Rev. 2 1-digit sectors (C to N), but for Financial Services and Real Estate (K and L). Source: National Accounts, Eurostat.

The dynamics depicted in figure 3, however, masks a great deal of across-sector heterogeneity. In figure 4, panel (b), we plot for Italy the markups series for each NACE Rev.2 sectors. Markups differ substantially, both in levels (e.g., ICT shows an average 1.3 against a more modest 1.15 for trade) and

Table 1: Descriptive Statistics: National Accounts and AMECO

	Full Sample			2006-2018		
Panel (a): Italy						
	mean	p50	sd	mean	p50	sd
Components						
Gross Output[a]	385.0	249.0	323.2	408.8	261.1	343.0
Value Added[a]	131.4	101.7	76.4	137.2	97.5	78.2
Labor Cost[a] - Hour Correction	90.2	83.5	52.7	97.1	83.1	54.7
Capital[a] - Current Prices	24.9	16.1	19.2	26.8	17.9	20.9
Markups						
$\tilde{\mu}^{lerner}$	1.157	1.129	0.075	1.139	1.109	0.067
$\tilde{\mu}^{lerner}$ - Industry	1.118	1.104	0.066	1.108	1.092	0.060
$\tilde{\mu}^{lerner}$ - Services	1.186	1.180	0.067	1.162	1.145	0.062
LT IR deflator	88.499	92.723	10.783	96.481	98.481	4.073
Panel (b): Germany						
	mean	p50	sd	mean	p50	sd
Components						
Gross Output[a]	728.9	347.4	652.7	824.6	404.9	719.5
Value Added[a]	275.2	193.4	198.3	304.4	228.7	216.2
Labor Cost[a] - Hour Correction	193.1	168.7	133.1	210.1	177.6	141.0
Capital[a] - Current Prices	48.2	26.0	39.9	53.2	29.6	43.2
Markups						
$\tilde{\mu}^{lerner}$	1.166	1.128	0.116	1.155	1.133	0.090
$\tilde{\mu}^{lerner}$ - Industry	1.128	1.113	0.082	1.135	1.122	0.075
$\tilde{\mu}^{lerner}$ - Services	1.203	1.165	0.132	1.174	1.165	0.100
LT IR deflator	92.720	90.366	6.446	96.381	97.001	5.768
Panel (c): France						
	mean	p50	sd	mean	p50	sd
Components						
Gross Output[a]	292.0	217.0	217.3	353.2	282.4	222.3
Value Added[a]	117.8	105.7	64.4	142.2	134.7	60.3
Labor Cost[a] - Hour Correction	84.4	81.6	44.7	104.4	106.7	44.0
Capital[a] - Current Prices	21.1	15.9	15.9	26.3	20.2	16.7
Markups						
$\tilde{\mu}^{lerner}$	1.154	1.128	0.108	1.136	1.119	0.063
$\tilde{\mu}^{lerner}$ - Industry	1.141	1.121	0.127	1.116	1.109	0.054
$\tilde{\mu}^{lerner}$ - Services	1.163	1.137	0.093	1.148	1.134	0.066
LT IR deflator	82.407	81.146	15.206	96.827	98.120	3.716
Panel (b): Spain						
	mean	p50	sd	mean	p50	sd
Components						
Gross Output[a]	199.4	127.0	152.9	218.0	189.5	160.1
Value Added[a]	74.9	67.3	38.9	82.3	87.6	40.0
Labor Cost[a] - Hour Correction	49.8	44.2	27.7	55.0	53.1	28.9
Capital[a] - Current Prices	13.2	13.6	7.8	13.9	14.2	8.4
Markups						
$\tilde{\mu}^{lerner}$	1.187	1.146	0.105	1.176	1.142	0.085
$\tilde{\mu}^{lerner}$ - Industry	1.176	1.130	0.118	1.182	1.135	0.107
$\tilde{\mu}^{lerner}$ - Services	1.195	1.157	0.094	1.171	1.151	0.065
LT IR deflator	97.968	100.000	11.874	105.454	106.679	4.650

Notes: National Accounts data 1996-2018 (source: Eurostat). Industry and Services but Financial and Real Estate (*BASE* sample). In columns 1 to 3 we report the mean, the median and the standard deviations of the variables of interest in the 1996-2018 period; in columns 4 to 6, for the same variables, we restrict the attention to the 2006-2018 period. The reported values of *Labor Cost* have been corrected *per hour* in order to account for self-employees in the sector. *Industry* includes NACE sectors C, D, E and F, *Services* includes sectors G, H, I, J, M, N (*BASE*). All measures are value added-weighted means at the sector-time level.
[a] In billion €.

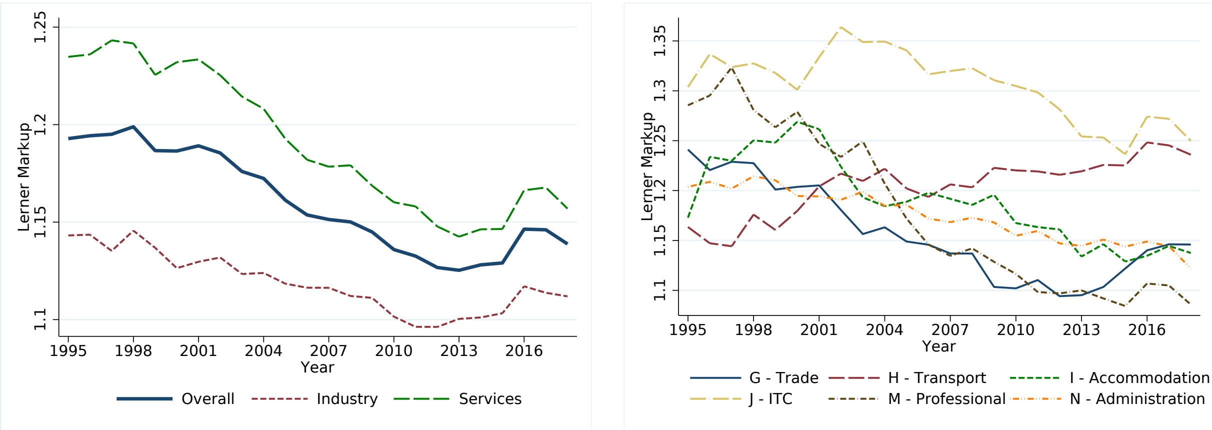
in trends (with e.g. increasing markups for the Transportation sector and strongly decreasing ones for the Professionals, whose relative rank moved from the second in 1995 down to being the lowest in 2018).

In figure 4, panel (a), we report, again only for Italy, the aggregated series for the whole country and for Industry and Market Services, separately. The dissimilarity between the two macro sectors regards the starting levels, but the marked decrease in Services' markup flattens the differences. Indeed, despite a qualitatively similar dynamics between the components, the aggregate trend is mainly driven by Services, also reflecting the higher value added share of this sector in the total economy.

Figure 4: Macro-aggregates and sector-level (Services) markups, Italy 1995-2018

(a) Aggregated Markups

(b) Sector-level markups in Market Services



Notes: (a) aggregate and Industry/Services components μ_t^{Lerner} in Italy, 1995-2018; (b) μ_{st}^{Lerner} for Market Services sectors in Italy, 1995-2018 (Nace rev. 2 sectors G, H, I, J, M and N).

In table 2 we report, for Italy and three comparable countries, the changes in markups for three periods. In column 1, we use the full time span (1995-2016),[8] whereas in columns 2 and 3 we split the sample in two sub-periods, roughly of the same length, 10 years. The evidence emerging from the table confirms the graphical evidence. In all four countries, the overall economy experiences a decline in markups (with the exception of Spain, total economy, between 2005 and 2016). The economy-wide trends are driven by the relatively marked decreases recorded in the Services sectors, whereas the Industry component shows less definite patterns, with all values near zero.

Roeger Estimation and Lerner robustness check We now turn to a different measure of markups. In particular, in order to estimate equation (1), we use the National Accounts coupled with the AMECO data to build the following measures

- $(\Delta p_t + \Delta Q_t)$: the output growth is $\frac{\partial Y_t}{\partial t} Y_t$
- $(\Delta w_t + \Delta N_t)$: the wage bill growth is $\frac{\partial \tilde{L}_t^H}{\partial t} \widetilde{LaborCost}_t^H$
- $(\Delta m_t + \Delta M_t)$: the intermediate input costs growth is $\frac{\partial Input_t}{\partial t} Input_t$
- $(\Delta r_t + \Delta K_t)$: the capital costs growth is $\frac{\partial Capital_t}{\partial t} Capital_t$

[8]While the National Accounts are available for Italy and Germany until 2018, the data for Spain and France only cover until 2016.

Table 2: Lerner Markup: Cross-country comparison

Country Sector	$\Delta\mu^{Lerner}_{16-95}$	$\Delta\mu^{Lerner}_{16-05}$	$\Delta\mu^{Lerner}_{05-95}$
Italy			
Industry	-0.02	0.01	-0.03
Services	-0.07	-0.03	-0.04
Total Economy	-0.05	-0.01	-0.03
Germany			
Industry	0.03	0.03	0.00
Services	-0.12	-0.05	-0.07
Total Economy	-0.04	-0.01	-0.03
France			
Industry	-0.01	-0.00	-0.01
Services	-0.07	-0.05	-0.02
Total Economy	-0.06	-0.04	-0.02
Spain			
Industry	0.03	0.02	0.01
Services	-0.11	-0.01	-0.10
Total Economy	-0.06	0.02	-0.08

Notes: for each of the four EU countries, the table reports the average changes in Lerner markups in the sample period (1995-2016, column 1), and in two subperiods (2005 to 2016 in column 2 and 1995 to 2005 in column 3). The figures are reported for the two macro components and for the baseline sample.

- α_{X_t}: the factor shares are $\frac{X_t}{Y_t}$, for wages and intermiate input

at various aggregation levels, for each country/year couple.[9] In table 3 we contrast the estimated Roeger markups ($\hat{\mu}^{Roeger} = \frac{1}{1-\hat{\beta}^{Roeger}}$) with the average values of the Lerner markup in Italy both for the full sample period, and for a reduced 12-year window (2006-2018). The results can be summarized as follows: i) the two measures, which are different in terms of computation method and characteristics,[10] display weakly correlated figures - in terms of pairwise correlations for Industry and in the first time span, while they seem to match more for the service sectors and in more recent years; ii) the industry sectors (C, D, E and F) show lower markups than market services according to both metrics.[11]

3.3 Within and Between Decomposition

We complement the analysis by investigating the driving channels of the markup dynamics. In particular, by disentangling cross-sectional and time variations we determine whether, and to what extent, changes in aggregated markups are driven by adjustments *within* the sectors, or by variations in the average

[9] More specifically, we use sector-level, economy-wide aggregates (value added-weighted) and macro components (Industry or Services).

[10] Roeger markups are time-invariant estimated parameters, whereas the reported Lerner markups are average accounting measures.

[11] With the exception of the energy market. In that sector, however, finding higher-than-average markups does not come as a surprise, given that they are typically heavily regulated (see e.g. the EU Regulation 2019/943 on the internal market for electricity. This is in line with previous contributions - see e.g. Thum-Thysen and Canton (2015); Rizzica, Roma and Rovigatti (2020) who highlight the correlation between the regulation on the one hand, and the level of markups and economic activity on the other.

Table 3: Lerner and Roeger markups, Italy 1996-2018 and 2006-2018

NACE Sector	1996-2018 $\hat{\mu}^{Roeger}$	1996-2018 $\bar{\mu}^{Lerner}$	ρ	2006-2018 $\hat{\mu}^{Roeger}$	2006-2018 $\bar{\mu}^{Lerner}$	ρ
Industry	1.12	1.12	-0.29	1.13	1.11	0.2
C	1.12	1.10		1.12	1.09	
D	1.09	1.35		1.16	1.31	
E	1.02	1.15		1.01	1.16	
F	1.16	1.09		1.14	1.08	
Mkt Services	1.36	1.19	0.21	1.29	1.16	0.46
G	1.35	1.15		1.42	1.12	
H	1.19	1.21		1.14	1.22	
I	1.52	1.18		1.43	1.16	
J	1.54	1.3		1.62	1.29	
M	1.49	1.17		1.21	1.11	
N	1.18	1.17		1.13	1.15	
Aggregated	1.18	1.16	0.17	1.15	1.14	0.32

Notes: Roeger and average Lerner markups in Italy for two different periods, namely the full sample 1995-2016 (columns 1 to 3) and 2006-2018 (columns 4 to 6). We report the two measures at the sector, macro components (Industry and Market Services) and aggregate levels. For macro-sectors and aggregates, we also report the pairwise correlations (ρ).

weight of the sectors (*between*). In order to do that, we decompose the changes in markups as follows

$$\Delta\mu_t = \mu_t - \mu_{t-z} = \underbrace{\sum_{s=1}^{S} sh_{st}(\mu_{st} - \mu_{st-z})}_{within} + \underbrace{\sum_{s=1}^{S} \mu_{st-z}(sh_{st} - sh_{st-z})}_{between} \tag{2}$$

where sh_{st} and μ_{st} are the share of total value added and Lerner markup of sector s respectively. We propose three different versions of equation (2), with different lengths of the time step $z = 1, 3, 5$. In order to investigate the relative importance of the two channels, for each model we regress $\Delta\mu_t$ alternatively on the within and between components, and report the results in table 4. Results show that the variation in the markups level is entirely due to the within component, whose weight on the markups adjustments is greater than 90% in all but one cases. In turn, the (slight) adjustments in the aggregate markups appears to be driven by structural characteristics and dynamics within sector, rather than by the reallocation of value added shares across sectors with different markups level.

Similar results are obtained, when the same analysis is conducted for Germany, France, and Spain. Despite slight differences in the amount of variation explained by the within component (from the virtual 100% of Italy and Germany, to level of $\approx 90\%$ in France at $\Delta t = 3$), all results comply with a model of nearly-static cross-sectoral shares, and strong movements of within-industry markup distributions. In order to investigate the latter, however, the analysis of aggregated data would be an unsuitable tool. National accounts data, indeed, prove inadequate capturing within-sector (or within-industry) dynamics. In order to strengthen the analysis, hence, we must shift our focus to firm-level data.

4 Micro Evidence: the Italian case

Our main micro-data source covers the universe of Italian firms in the private non financial business sector (ASIA-Frame, henceforth). The dataset has the advantage to provide high quality data, not

Table 4: Within and between decomposition of markups changes

Country		$\Delta t = 1$		$\Delta t = 3$		$\Delta t = 5$	
		within	between	within	between	within	between
Italy							
	$\Delta\mu^{Lerner}$	0.994***	0.00644	1.016***	-0.0156	1.040**	-0.0402
		(0.0318)	(0.0318)	(0.0413)	(0.0413)	(0.0901)	(0.0901)
Germany							
	$\Delta\mu^{Lerner}$	1.049***	-0.0492	1.017***	-0.0171	1.264*	-0.264
		(0.0387)	(0.0387)	(0.0795)	(0.0795)	(0.214)	(0.214)
France							
	$\Delta\mu^{Lerner}$	0.958***	0.0417	0.905***	0.0952	0.847***	0.153**
		(0.0334)	(0.0334)	(0.0497)	(0.0497)	(0.00803)	(0.00803)
Spain							
	$\Delta\mu^{Lerner}$	0.962***	0.0377	0.939***	0.0607	0.923**	0.0769
		(0.0201)	(0.0201)	(0.0611)	(0.0611)	(0.0890)	(0.0890)

Notes: Within and between channels weights on $\Delta\mu_t^{Lerner}$, for different values of Δt (1 year, 3 years or 5 years) and four EU country.

biased in favour of firms with specific characteristics (for instance, bigger or listed firms). As we do not have access to comparable data-sets for other European countries, from now on we will restrict our focus to Italy only. The main cons of ASIA-Frame are that it is available for a rather limited period of time (since 2011) and only includes a limited number of balance-sheet variables - e.g., the variables reporting total assets or investment are absent. This limitations implies that we cannot estimate markups using the production function based methodology recently proposed by the well cited De Loecker and Warzynski (2012) (DLW, henceforth) and De Loecker, Eeckhout and Unger (2020), and directly compare our findings with theirs.

Therefore, we employ a second data source that covers the universe of limited liability companies (CERVED, hencefort), which annually must submit by law their balance sheet to the chamber of commerce.[12] The CERVED dataset has the key advantages of covering a longer time period (2004 to 2018)[13] and to provide a great deal of detail in the accounting variables, allowing for the estimation of production function elasticities. Despite these advantages, the main drawback of the CERVED data is its limited and selected coverage of firms (about 50% of firms), which can be particularly relevant in the non-manufacturing sector (e.g. it covers only about 30% of firms in the accommodation and restaurant and professional services sector). While the limited coverage is severe in terms of number of firms – and hence can be problematic if the aim of the analysis is to study the distribution of markups – it is much less of a critical issue as of representativeness, in terms of both employment and value added, thus still making this data suitable to study the evolution of aggregate markups (see table BB.1 for further details).

[12]This data is the Italian version of the ORBIS BVD data available also for many other countries.

[13]The dataset coverage is much longer, but do to the 2003 reform on corporate law, the time series is consistent starting from 2004.

4.1 Analisys based on ASIA-Frame data

Data description, variable definition and sample selection

The ASIA-FRAME dataset is an integrated firm-level dataset covering all firms active for at least 6 months in a given business year, developed at the National Statistical Agency (ISTAT). The dataset contains information on industry classification (NACE), number of persons employed, labor costs, turnover, intermediate input costs and value added. As for most firms information on investment and capital is not available, we are unable to use this data for estimating a production function and we measure markups at the firm level using the Lerner index. This methodology follows, with some adjustments imposed by the nature of the data, the one used in section 3.1, easing the comparison between a micro- and a macro-based approach in the estimation of markups.

In particular for each firm i and each year t in our data we measure the Lerner index as:

$$Lerner_{it} = \frac{ValueAdded_{it} - LaborCost_{it} * \frac{PersonsEmployed_{it}}{Employee_{it}}}{Revenues_{it}} \tag{3}$$

where at numerator we proxy the GOM by subtracting from value added the labor costs paid by the firms adjusted by the ratio of total person employed over employee, in order to correct for the fact that some workers might not receive a compensation in the form of a wage, as discussed in section 3.1.[14] This definition of the Lerner index imposes the first restriction in the use of our data, in particular, the Lerner index can be consistently measured and compared across firms only when labor costs are strictly positive, that is when the firms employ at least one paid employee.[15] Notice also the the Lerner index from a theoretical point of view cannot be neither negative nor greater than one (which in turns implies that markups measured using the Lerner index cannot be lower than 1). While this is true in theory, it might not hold in practice, for example because value added can be negative and/or labor costs can be higher than value added. For this reason we impose a further restriction on our data, that is we select only firms with $Lerner \in [0, 1)$, setting it equal to zero for all firms with negative values. Finally, we measure markups for each firm as $\mu_{it}^{Lerner} = \frac{1}{1-Lerner_{it}}$ and to reduce the influence of outliers we drop the markups for firms above the 99 percentile.[16]

Table 5 shows some descriptive statistics about the ASIA-FRAME data. In the first column of the first panel, we report for each sector the average number of firms. The second column reports the value added of firms in our sample, while the third column the number of workers employed by the firms. The fourth column shows the value of total sales for firms in our sample. The last two columns display the simple mean of the Lerner index and of the associated markups.

As a first step in our analysis, in Figure 5 we show the distribution of markups by firm characteristics. In the top left panel (a) we plot the share of firms with unit markups -i.e. those firms that charge prices

[14] An employee is a person who works for an employer on the basis of a contract of employment and receives compensation in the form of wages or salaries. The persons employed by a firm instead also include working proprietors, partners working regularly in the unit and unpaid family workers.

[15] As an example suppose that there are two firms a and b with the same revenue, value added and number person employed. The only difference between a and b is that a employ only people that work on the basis of a contract and receive a wage, while in b work only proprietors that do not receive a compensation in the form of wage. Because the labor costs is positive for firm a and zero for firm b, the Lerner index (and hence the markups) is lower for firm a, even if the *actual* compensation received by the proprietors of firms b is the same of that of the employee of firm a.

[16] Even if we consider only firms with Lerner index in the interval $[0, 1)$ there are still some implausible markups measure in our data, one possible reason is the presence of measurement error. Following De Loecker, Eeckhout and Unger (2020) we drop observations only on the right tail of the distribution.

Table 5: ISTAT Data - Descritptive statistics

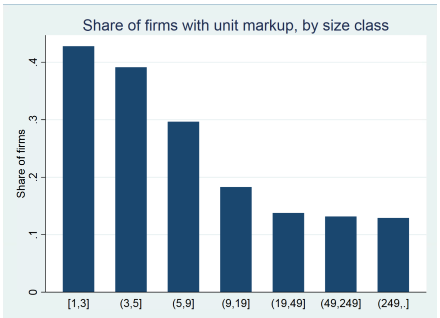
NACE Rev.2 sector	Firms	VA (000)	Workers	Sales (000)	$\hat{LI}_{it}$	μ^{Lerner}
C - Manufacturing	214,820	1,090	16	4,543	0.08	1.11
F - Construction	153,380	266	6	875	0.07	1.09
G - Trade	338,491	362	8	2,980	0.05	1.06
H - Transport	50,830	847	17	2,594	0.06	1.08
I - Accommodation	209,773	153	67	394	0.06	1.08
J - ITC	38,079	1,288	14	2,986	0.11	1.15
M - Professional	105,413	355	6	880	0.21	1.39
N - Support	567,78	730	23	1,669	0.11	1.17

Notes: Total number of firms (column 1) and simple averages of Value added (in thousand €), number of workers, total sales (thousand €), Lerner Index and Lerner markup per NACE Rev. 2 sector. All values refer to 2018. Source: ASIA-Frame, Istat.

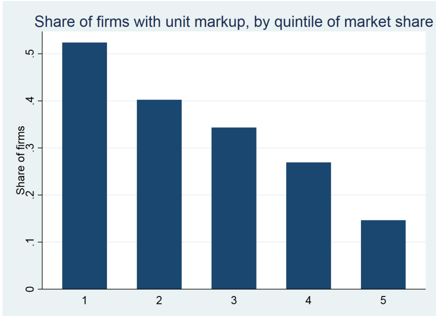
equal to their marginal costs- by class size (measured in terms of worker headcounts). The share of firms with unit markups is decreasing in firm size: while up to 40% of firms with less than 3 employees have unit markups, the share falls to about 10% for larger firms. This is consistent with the existing evidence that larger firms charge higher markups (De Loecker and Warzynski, 2012; Autor et al., 2020). The top right panel (b) shows the share of firms with unit markups by quintiles of the within industry distribution of market shares. Firms with smaller market share charge more frequently unit markups than those owing higher shares, an implication that can be found in several macro models with variable markups (Atkeson and Burstein, 2008). The two plots at the bottom (panel c and d) show the percentage of firms with markups below the within 4-digit industry median: smaller firms in terms of both employees and revenues tend to charge lower markups. Taken together the evidence suggests that with our measure of markups at the firm level we are able to replicate well established stylized facts from the existing literature, suggesting the suitability for further investigation of the role of firm level heterogeneity in determining aggregate markup dynamics.

Figure 5: Markups level and firm characteristics

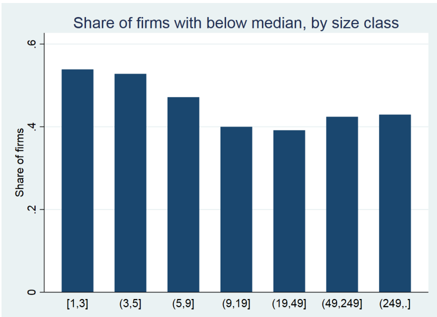
(a) By size class



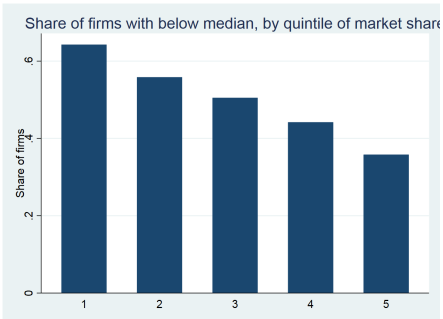
(b) By quantile of mkt share



(c) By size class



(d) By quantile of mkt share



Notes: (a) share of firms with unit markup divided by size - according to the number of employees; (b) share of firms with unit markup divided by quantiles of market share; (c) share of firms with markups below the median value divided by size - according to the number of employees; (d) share of firms with markups below the median value divided by quantiles of market share. Source: Istat ASIA-Frame.

The evolution, distribution and decomposition of markups using ASIA-FRAME

Figure 6 shows aggregate markups computed using firm level ASIA-FRAME data. Following recent contribution in the literature (De Loecker, Eeckhout and Unger, 2020; Autor et al., 2020), aggregate markups in each sector is defined as a sales weighted average of firm markups, i.e.:[17]

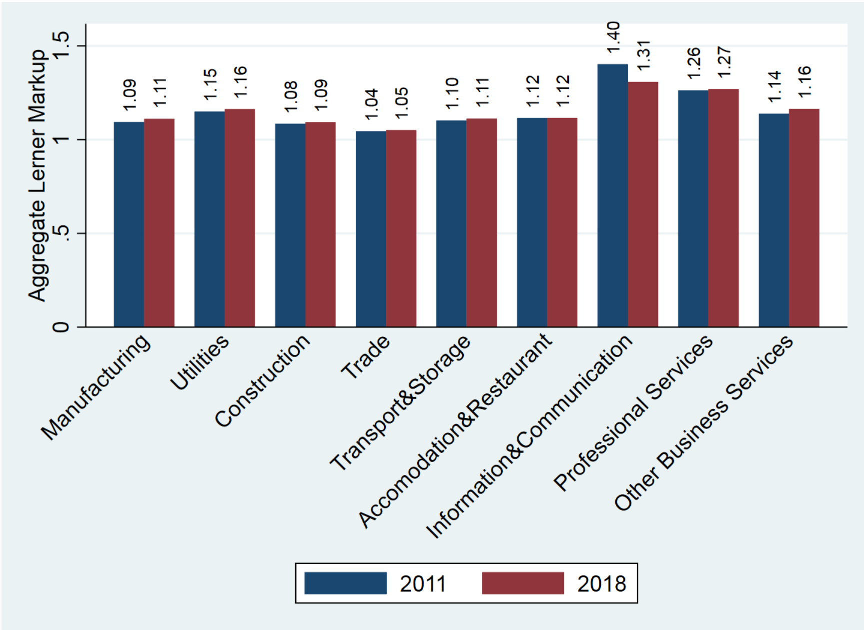
$$\mu_{st}^{Lerner} = \sum_{i \in s} \mu_{it}^{Lerner} \omega_{it} \tag{4}$$

where ω_{it} is the revenue share of firms i in sector s at time t. Both the level and the dynamic of aggregate markups measured using micro data are remarkably similar to those estimated using aggregate data in the first part of the paper (see table 3), with markups larger on average in some service sectors.

As a next step in our analysis, we start exploring the role of firm heterogeneity by looking at the evolution of different percentiles of the markup distribution over time (see figure 7). For each sector we take aggregate markup, the median and the 75th and the 90th percentiles. In all sectors, all moments of the markups distribution are decreasing in the first years of analysis. This dynamic reflects the fact that, at the beginning of our sample period, the Italian economy was slowly recovering from the global

[17]Notice that in the analysis with macro data we use value added weights, while here we use sales weigthed markups. While in the macro framework the choise of VA-based weights is dictated by the need of higher homogeneity in sector comparison (in particular between Industry and services, given the very different importance of cost of materials), in the present context, there are two reasons for choosing sales-based weights. First, value added at firm level can be negative, thus making its use problematic when aggregating firm level markups. Second, the recent literature on firm-level markups estimation uses sales-based weights, thus making our choice more useful for comparison reasons.

Figure 6: Aggregate markups by sector



Notes: average μ^{Lerner} per NACE Rev. 2 sector in 2011 (blue bars) and 2018 (red bars). Source: Istat ASIA-Frame.

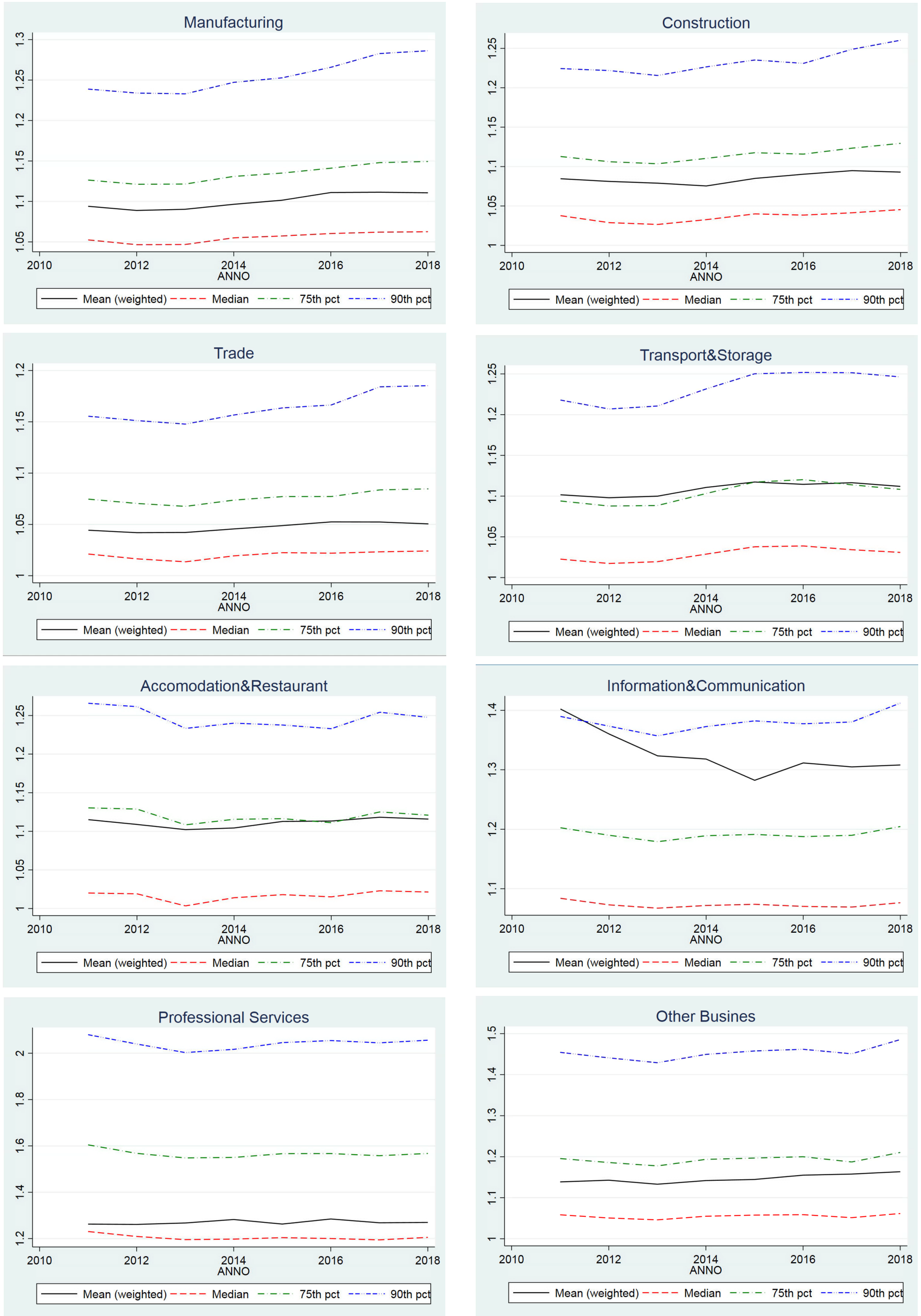
financial crisis (henceforth, GFC), while quickly entered the Sovereign Debt Crisis. Not surprisingly, in almost all sectors, the largest adjustment occurred a the top of markups' distribution (90th percentile), in part reflecting marked initial differences in the level of markups. Interestingly, however, the dynamics of markups were heterogeneous across sectors afterwards. While in most sectors markups at the 90th percentile were about 2-3 percent higher in 2018 than in 2011, in the accommodation and restoration and in the professional services sectors they were below their initial levels. In those two compartments, all the moments of markups' distribution have decreased and never recovered throughout our sample period, indicating a permanent shift in the overall distribution.

Having characterized the evolution of the overall markups distribution, we now want to understand what drives the dynamics of aggregate markups at the firm level. In particular, to what extent changes in markups reflect dynamics within the firm or changes in sales shares between firms with different markups levels. To this end we apply the following decomposition:

$$\Delta\mu_t = \underbrace{\sum_i \omega_{i,t-1}\Delta\mu_{it}}_{\Delta within} + \underbrace{\underbrace{\sum_i \tilde{\mu}_{i,t-1}\Delta\omega_{i,t}}_{\Delta marketshare} + \underbrace{\sum_i \Delta\mu_{i,t}\omega_{i,t}}_{\Delta cross\, term}}_{\Delta reallocation} + \underbrace{\sum_{i\in Entry} \tilde{\mu}_{i,t}\omega_{i,t} - \sum_{i\in Exit} \tilde{\mu}_{i,t-1}\omega_{i,t-1}}_{net\, entry} \quad (5)$$

Following Haltiwanger (1998), the "within" term measures the average change that is merely due to a change in the markup of incumbent firms, while keeping market shares fixed; the "market share" component captures the variation induced by an increase in the market share of incumbents, while keeping markups unchanged. If the latter term is increasing, firms with higher markups acquire market shares over time and therefore weigh gradually more in the aggregate. In turn, this raises the average markup without raising firm-level values. The "cross term" measures the joint change in markups and market

Figure 7: Percentiles of markups distribution

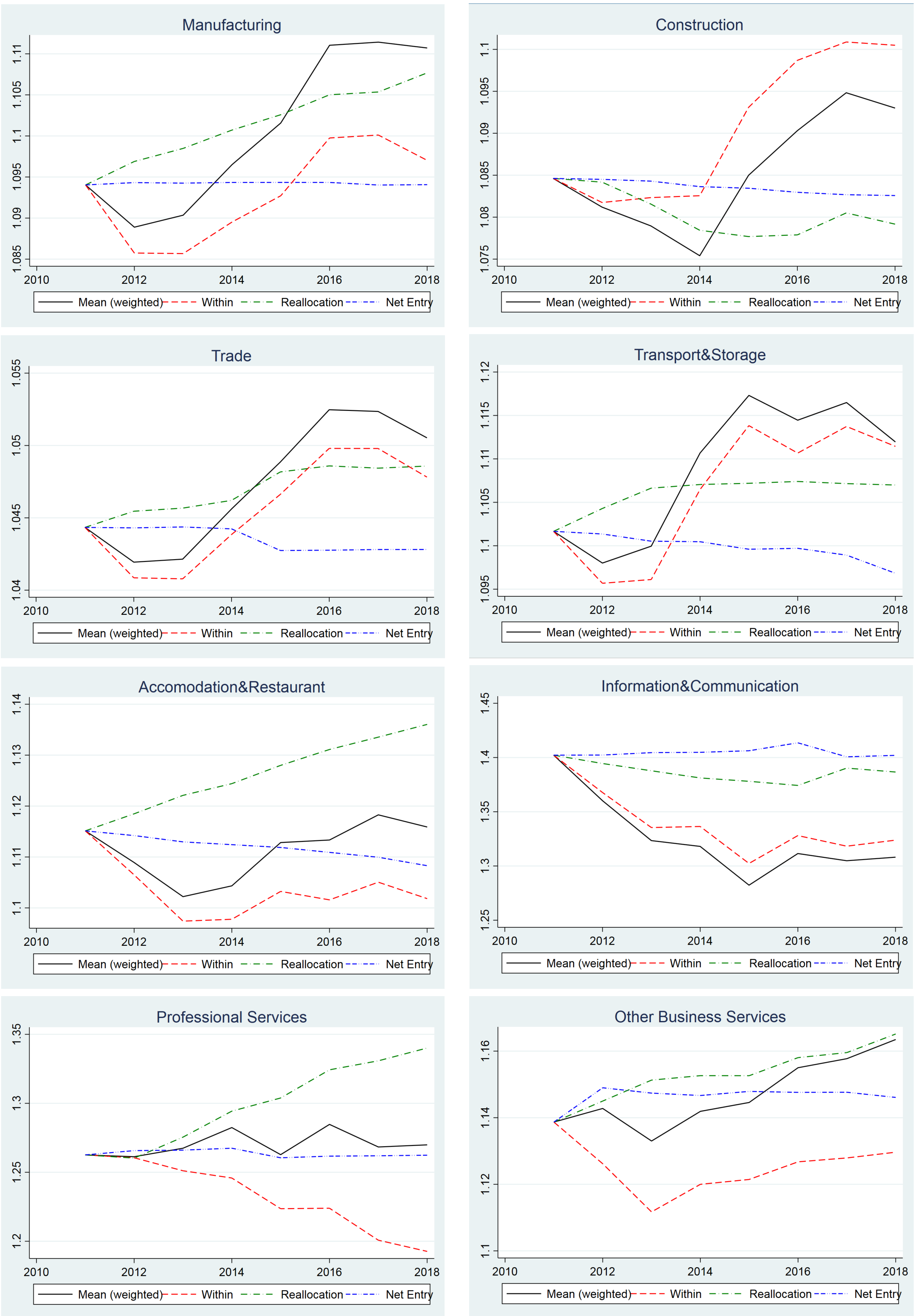


Notes: weighted mean, median, 75^{th} and 90^{th} percentile of μ^{Lerner} per sector. Source: Istata ASIA-Frame.

shares of incumbents. The sum of these terms is usually defined as the "reallocation effect". Finally, the last 2 components account for the variation associated to entry and exit and capture the change in the composition of firms in the market. Figure 8 summarizes the results. For each sector, we plot the sales weighed aggregate markups and three counterfactual exercises based on the decomposition, that is we set the initial level of markups in 2011 and for each of the three component we add cumulative changes. Each counterfactual represents what would have been the evolution of markups if only one component had actually materialized during the sample period (e.g. the within line represents what would have been the aggregate markups dynamics in a scenario with only the observed within adjustments, with neither reallocation nor net entry).

In all sectors, markups adjustment at the firm level (the "within" component) exhibit the largest variation, indicating that pricing behavior of firms is an important determinant of markups dynamics. Moreover, in all sectors, within firm markups follow a cyclical pattern: they decrease in the first year of the analysis and recover afterwards. The reallocation component, i.e. the increase in market share of high markup firms, sustained the evolution of markups in all sectors but constructions and information & communications, where their overall contribution at the end of our sample period was negative. Finally, the overall contribution of net entry has been negligible in all sectors. Despite the differences in the methodology and the rather limited time window of the analysis, our results suggest the micro dynamics of markups in Italy are rather different from those observed recently in the US. First, as documented in the previous section with aggregated data, markups remain quite stable over the last decade. Second, while the reallocation of market shares towards high markups firms sustain markups dynamics, their positive contribution remain quantitatively limited. Finally, the within-firms component seems the most relevant in explaining markups patterns. While in the US, for the same time period, De Loecker, Eeckhout and Unger (2020) show that the aggregate markups growth is almost entirely steered by the reallocation component, our analysis suggests that no top-firms trends emerge.

Figure 8: Decomoposition of markups at firm level



Notes: Average μ^{Lerner} per sector (black solid line) decomposed into the *Within*, *Reallocation*, and *Net Entry* components as in (5). Source: Istat ASIA-Frame.

4.2 Analysis based on CERVED data

The analysis presented in this subsection is based on balance-sheet data for the universe of limited liability companies in Italy, provided by Cerved Group. As already mentioned, the main advantages of using this data-set are that it dates back to 2004 and provides us with the variables required for the estimation of markups according to De Loecker and Warzynski (2012) and De Loecker, Eeckhout and Unger (2020).

For each firm, we extracted the book value amount of physical and immaterial capital, value added, revenues, cost of labor, depreciation, investments and divestment, the expenditure in intermediate goods and services. Balance-sheet information are integrated with employment and wages data from INPS, several firm demographic information from Infocamere, the Italian business register, and ISTAT National Accounts sectoral statistics for capital depreciation. In accordance with the previous analysis, we keep only firms in manufacturing, constructions and private services, excluding financial and insurance services and real estate activities.[18] We use this data-set to compute markups first from the Lerner index and then from the production-function estimation. In this way we can compare the results to those obtained in the previous sections, taking into account both the use of different data and the implementation of a different approach.

4.2.1 Lerner-based markups

In line with equation (3) above, the Lerner index is defined as:[19]

$$Lerner_{it} = \frac{ValueAdded_{it} - LaborCost_{it}}{Revenues_{it}}$$

and the firm-level markup is given by $\mu_{it}^{Lerner} = \frac{1}{1-Lerner}$. As we did for the ASIA-FRAME data, we set $Lerner_{it} = 0$ whenever negative, such that $Lerner \in [0, 1)$ and $\mu_{it}^{Lerner} \geq 1$. In this setting we cannot implement the correction for the incidence of self-employment due to data limitation. Table 6 reports some descriptive statistics for the data used in the analysis for year 2018: compared to table 5, firms in the manufacturing sector appear to be over-represented (26 per cent of the CERVED sample, compared to 18 percent in ASIA), while firms in accommodation activities and professional services tend to be under-represented (respectively 10 and 5 percent in CERVED, against 18 and 9 percent in ASIA). CERVED's firms are on average bigger, in terms of both sales and employees, and have a higher value added per worker. Despite these differences, in both samples the trade sector, which has a similar representation in the two data-set, has the lowest unweighted average markup, while ITC activities have the highest.

The evolution, distribution and decomposition of Lerner markups using CERVED

Figure 9 shows aggregate markups by sectors, computed according to equation (4). Results are overall in line with those obtained using the ASIA-FRAME population: markups are substantially constant over time and tend to be higher in some services: transports, telecommunications and business support services. On the contrary, the trade sector displays the lowest aggregate markups. Moreover, the slight

[18]Data are cleaned for outliers, winsorizing for the extreme values in the yearly growth rates of the main variables. We also drop observations firms that have labour costs equal to 0 and that do not have more than 1 employee.

[19]The dataset in this case does not allow us to correct for self employed.

Table 6: Cerved Data

NACE Rev.2 sector	Firms	VA	Workers	Sales	$\hat{LI}_{it}$	μ^{Lerner}
C - Manufacturing	97,762	2,092	25	9,571	0.12	1.15
F - Construction	51,711	554	10	1,878	0.13	1.17
G - Trade	100,195	818	12	7,793	0.07	1.08
H - Transport	21,949	2,122	28	5,758	0.11	1.16
I - Accommodation	41,116	415	15	1,045	0.12	1.16
J - ITC	19,057	1,517	17	4,041	0.16	1.24
M - Professional	20,370	785	11	2,467	0.16	1.25
N - Support	22,610	1,506	39	3,660	0.14	1.21

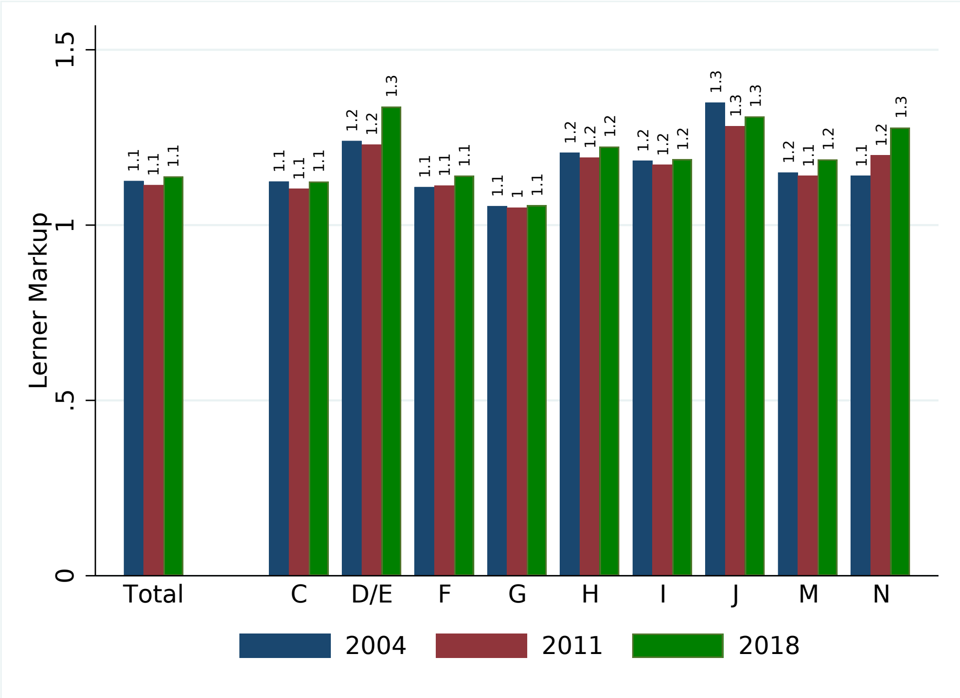
Notes: Total number of firms (column 1) and simple averages of Value added (in thousand €), number of workers, total sales (thousand €), Lerner Index and Lerner markup per NACE Rev. 2 sector. All values refer to 2018. Source: CADS, Cerved Group.

increase in markups at the end of the sample period appears to be an adjustment after the reduction observed after the GFC. Only transport and support services exhibit a modest increasing trend over the whole period.

The evolution of different percentiles of the markup distribution over time and for different macro-sectors is reported in figure 10. As already emphasized, markups in Italy are quite stable over time: all branches of economic activities show either a constant or a slightly decreasing trend in the first part of the sample, and, as for the ASIA-FRAME data, a small increase starting after 2012. Especially in constructions, the largest adjustment occurred a the top of the markups distribution (90th percentile).[20] In all sectors, the weighted mean is larger than the median, overlapping with the 75th percentile in services, suggesting that fewer firms with higher markups tend to have higher markets shares as well.

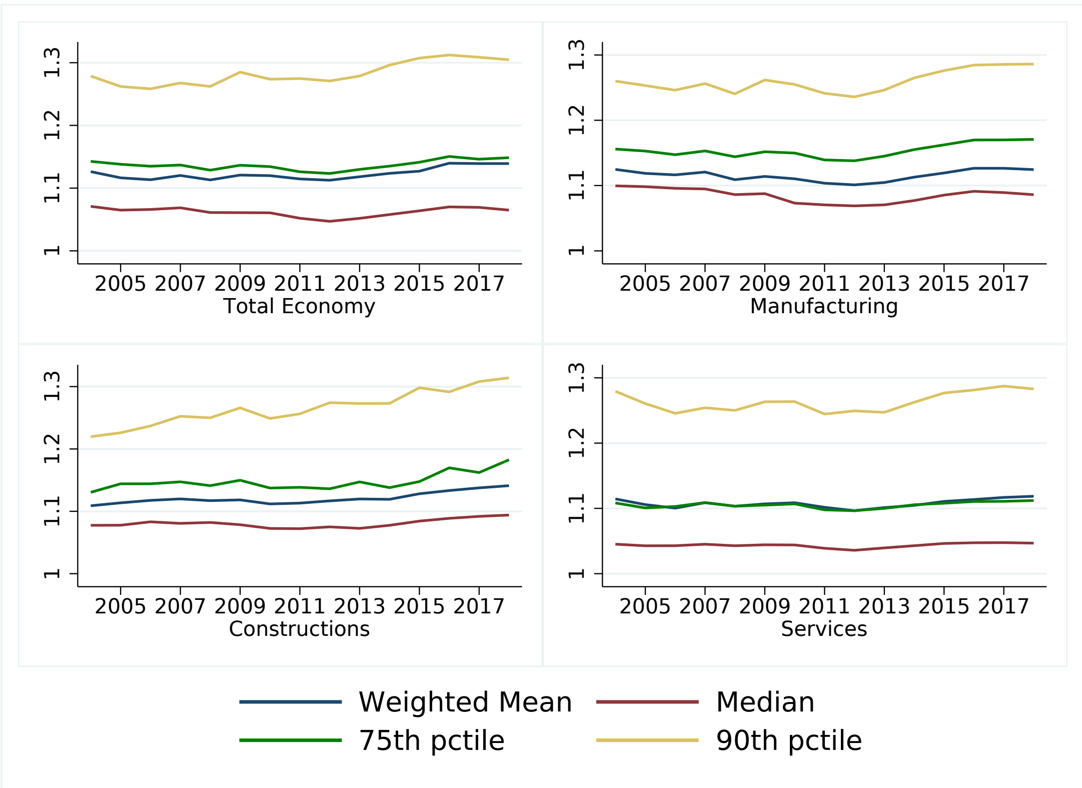
[20]This is particularly true for individual transport and support services (see fig. ABB.1 in Appendix). The constant medians suggests that the increase in markups has involved only few big firms with already high profit margins.

Figure 9: Aggregate markups by sector - CERVED sample



Notes: Average μ^{Lerner} in the whole country (*Total*) and per NACE Rev. 2 sector in 2004 (blue), 2011 (maroon), and 2018 (green bars). Source: CERVED Group.

Figure 10: Percentiles of the markup distribution

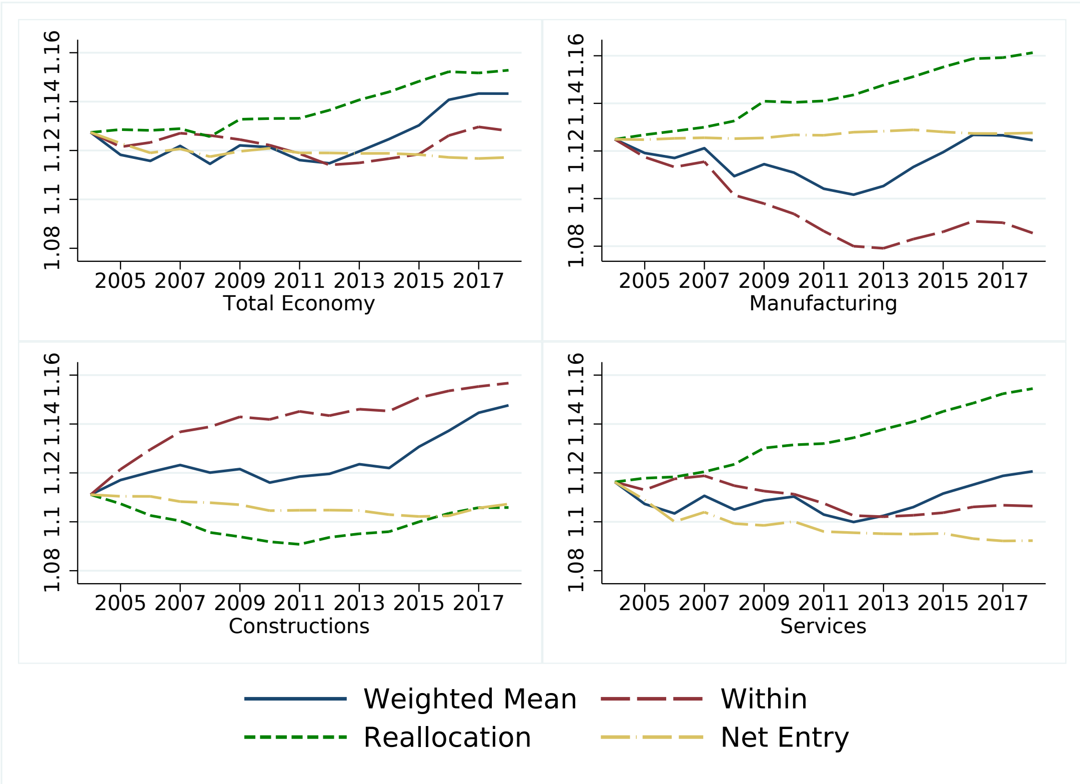


Notes: weighted mean, median, 75^{th} and 90^{th} percentile of μ^{Lerner} overall (*Total Economy*) and for the main aggregates. Source: CERVED Group.

The decomposition of markup changes also produces results similar to those obtained for the ASIA-FRAME data. For both manufacturing and aggregate services the "reallocation" components always provides a positive contribution, i.e. firms with higher markups have gained market shares over time. The variation of markups of incumbent firms, shaping the overall dynamics, is decreasing until 2012, and slightly increasing thereafter (see figure 11).[21] The constructions sector, instead, is characterized by a positive contribution of the "within" component throughout the entire period. The net-entry component appears always negligible.

Overall, we can conclude that the ASIA-FRAME and the CERVED data-sets, despite the differences in terms of coverage, provide a similar picture for both the levels and dynamics of Lerner-based markups. Moreover, these measures based on firm-level data are in line with those obtained with macro data and discussed in the previous sections (see figure 12).

Figure 11: Decomposition of markup dynamics



Notes: Average μ^{Lerner} per sector (black solid line) decomposed into the *Within*, *Reallocation*, and *Net Entry* components as in (5). Source: CERVED Group.

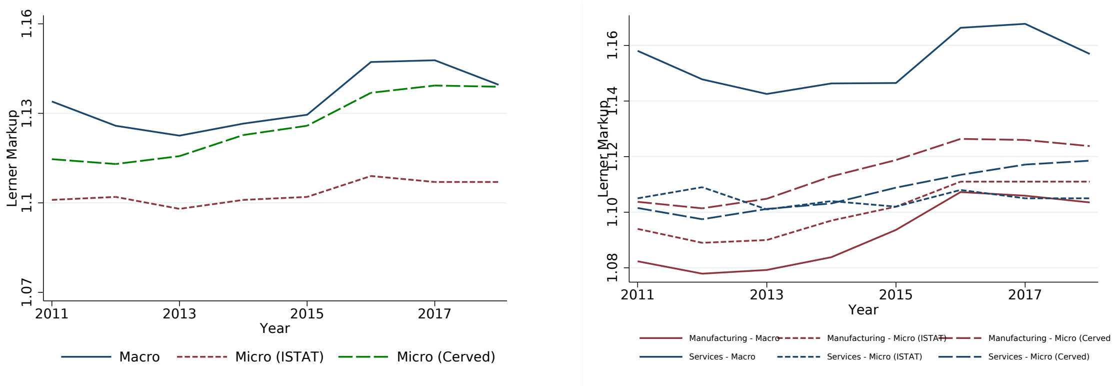
[21] Again, a similar pattern emerges also for individual service sectors (see figure ABB.2).

Figure 12: Comparison of Lerner-Based markpus

(a) All sectors

(b) Manufacturing and Services

Notes:



Average μ^{Lerner} computed at the macro and micro level (both with ASIA-Frame and with CADS data) for the whole economy - panel (a) - and for manufacturing and services - panel (b) . Source: National Accounts (Eurostat), ASIA-Frame (Istat), CADS (CERVED Group).

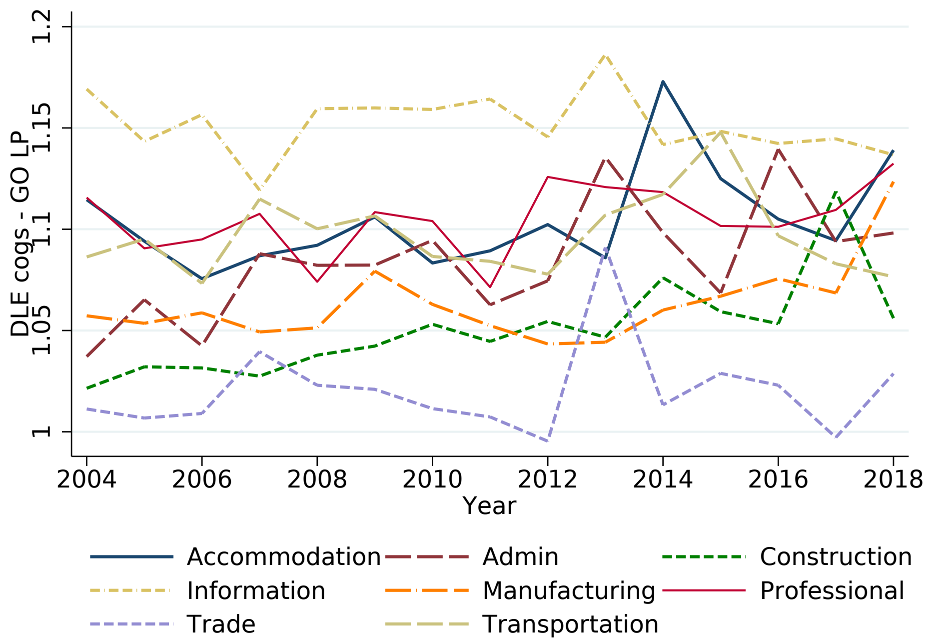
4.2.2 Production function-based markups

Since De Loecker and Warzynski (2012), the literature on markups estimation exploits the increasing availability of individual firms output and input data and is based, as in Roeger (1995), on the cost minimization problem faced by producers. A measure of the markup is thus obtained as the wedge between a variable input's expenditure share in revenues and the associated output elasticity, obtained by the production function estimation (see the appendix for more details). This approach, despite there are still many open measurement and econometric issues (see for instance Raval (2020) and Basu (2019)), has the advantage of not requiring to model demand and to impose any assumption on the extent of returns to scale. Using CERVED financial statement data, we follow De Loecker, Eeckhout and Unger (2020) and estimate for each sector of activity s and year t the parameters of a Cobb-Douglas gross output production function, where inputs are capital and a bundle of variable inputs, including both labour and intermediates (*Cost of Goods Sold*). The elasticity parameter obtained for the variable inputs $\beta^v_{s,t}$ is then used to compute the firm-level markup as:

$$\mu^{DLEU}_{it} = \beta^v_{s,t} \frac{Revenue_{it}}{Cost^v_{it}} \tag{6}$$

where $Revenue_{it}$ is the revenue and $Cost^v_{it}$ the cost of the bundle v. The aggregate markups for the different branch of activities are shown in figure 13. The level and the dynamics we obtain are overall in line with those for the other measures presented above. Markups are in general low (slightly above one) and roughly constant over time. Services tend to have higher markups, with the exception of trade services, which have the lowest. Support, ITC and transport services are those displaying the highest figures. Almost all sectors exhibit a moderate drop right after the GFC followed by a rebound.

Figure 13: DLEU (2020) markups by sector



Notes: Average μ_{DLEU} per sector in Italy, 2004-2018. The markups are computed as in (6). See appendix D for details on the estimator proposed by De Loecker, Eeckhout and Unger (2020). Source: CADS, CERVED Group.

Also for the production function-based markups, the different percentiles of the distributions tend to move together, with slightly more pronounced adjustments at the 90th. In terms of decomposition, as for the other measures, the within component is the one that drives the overall dynamics and the net entry component provides a very small contribution. The main difference with our previous results is that the reallocation brings either a null or a sightly negative contribution.[22]

[22] Results available upon request.

5 Comparison with Previous Contributions

In studying the dynamics of the "global market power", De Loecker and Eeckhout (2018) (DLE henceforth) estimate production-function-based markups using the same methodology as De Loecker, Eeckhout and Unger (2020) employing a firm-level dataset covering several countries. In doing so, they assume a common sector-specific production function across countries - the underlying idea being that firms competing in international markets would share on average the same technology. In other words, following equation 6, they apply the parameter β_s^v, estimated on US data, to all countries/regions, when computing firm-level markups. As we anticipated in the Introduction, they document a steady rise of global markups from around 1.17 in 1980 to about 1.6 in 2016. In Europe, the increase was around 60%, to above 1.6 in 2016. As for Italy, they find a rather high level of markups and one of the sharpest increase since the 1980s, concentrated in the first and last years of the time range. Thus, their results differ, quantitatively and qualitatively, from those we have presented in the previous sections. We argue that this discrepancy is due to two main sources of bias affecting their analysis, which massively influence the estimation in the Italian setting: a severe sample selection - only public listed companies are included- and the common technology assumption.

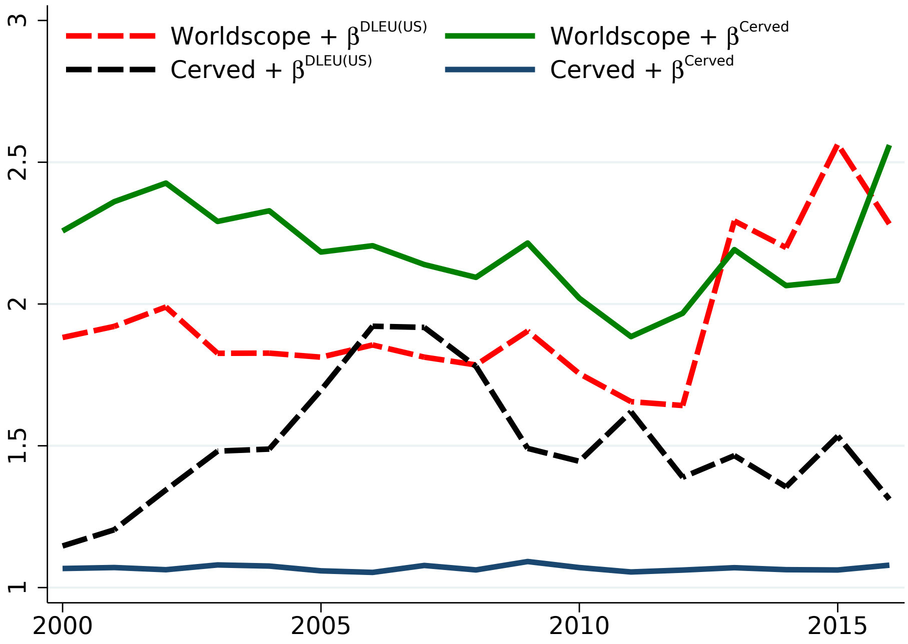
In figure 14, we report the markups estimated for Italy using two different firm-level datasets; (i) *Worldscope* - by Thomson Financial - which is the one employed in DLE, including only the listed companies; (ii) CERVED - that includes all capital-based and limited companies (see section 4.2.2 above). First, we replicate the DLE approach by using Worldscope data and the sector elasticities computed for the US by DLEU ($\beta^{DLEU(US)}$, red line). Despite the shorter time span - the data cover the 1995-2015 period only - our exercise roughly replicates the double spike that characterizes the original DLE plot, with the estimated markups peaking around 2000, and reaching 2.5 at the end of the analysis (see AA.1).[23] Second, we consider markups obtained by combining Worldscope data with the elasticities we estimated, at the sector-year level, using CERVED data (β^{Cerved}, green line). [24] Third, we go back to CERVED data and compute the aggregated markups by applying $\beta^{DLEU(US)}$ (black line). The dynamics obtained is now rather different from the previous ones, with a peak right before the 2008 financial crisis, and a decreasing trend to around 1.4 afterwards. Finally, we compare these results with aggregated markup previously obtained using both data and estimated parameters from CERVED (blue line). In line with the results presented throughout the paper, the series is basically flat at an average value right below 1.1.

The sizeable differences across the series may come from two sources, both relevant in driving the results. On the one hand, the selection of the sample: using a very specific type of firms - i.e., the public listed companies - may yield satisfactory results in countries like the US, where they represent a considerable share of total production and employment. In Italy, though, their number as well as relative size makes them poorly representative of the total economy. On average, Worldscope covers around 270 firms per year, with a total turnover that amounts to less than 1% of the yearly GDP (see table 7).

[23]In the appendix, figure AA.2 we use the same approach on a different dataset (Compustat, by Standard and Poor's) which, despite being in principle similar to Worldscope in terms of coverage and intended purpose, offers a rather different picture in terms of both the level and dynamics of average markups. In fact, although obtained using the very same βs, the series shows no peaks and a markup figure rather "static" below 1.4.

[24]In the original data, the sector-specific βs are computed according to the *International Standard Industrial Classification of All Economic Activities* (ISIC), whereas firms in the Wordlscope data are classified according to the *North American Industry Classification System* (NAICS). We match the two classifications using correspondence tables, and manually checking their comparability.

Figure 14: Aggregate markups: various datasets



Notes: Aggregate markups in Italy, 1995-2018, computed as in De Loecker and Eeckhout (2018) with Worldscope (red and green) and CERVED (black and navy). Source: Worldscope (Thomson Financial) and CADS (CERVED Group).

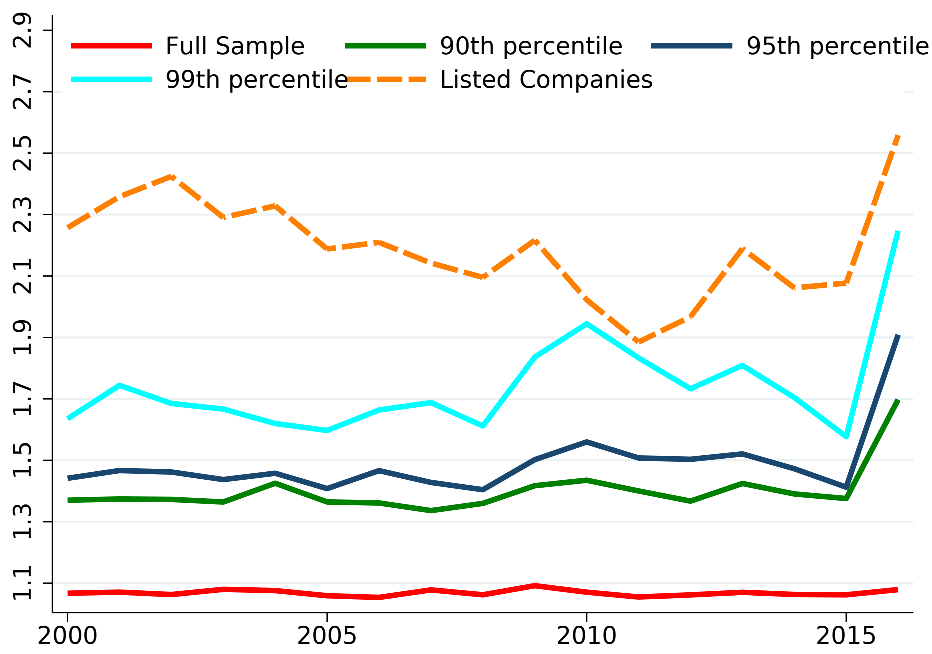
Table 7: Firm-level datasets: Descriptive Statistics

	Worldscope	CERVED
Revenues (mil.)		
Mean	2.160	.006
Median	.171	.001
Min	0	.000
Max	143.43	400.162
COGS (mil.)		
Mean	1.325	.005
Median	.0773	.001
Min	0	0
Max	113.303	43.992
COGS - share		
Mean	.509	.876
Median	.515	.930
Min	0	0
Max	1	1
Elasticities	$\beta^{DLEU(US)}$	β^{Cerved}
Mean	.825	.934
Median	.834	.929
Min	.696	.792
Max	.939	.998
Observations	3,410	4,507,296

Notes: Descriptive Statistics of the datasets used for the estimation of aggregate markups in Italy - 1995/2018. Source: Worldscope (Thomson Financial), CADS (CERVED Group).

On the other hand, the assumption of common elasticities, which might be plausible for certain sectors/countries, fails in the Italian context. Using $\beta^{DLEU(US)}$ generates an inverse-U dynamics that simply disappears whenever the production function estimation is performed on Italian data.[25] Using CERVED data, in figure 15, we contrast the (weighted) average markups obtained for firms belonging to different percentiles of the (markups) distribution - namely, the 90^{th}, the 95^{th} and the 99^{th} with the series of the listed companies, using own estimated elasticities (β^{Cerved}). The graph highlights a remarkable difference between our estimates based on the CERVED sample (red line) and those proposed by DLE, considering the listed companies sub-sample only (dashed orange line). Even when focusing on firms in the top 1 percent of the distribution (light blue line), the average estimated markup of the listed firms is higher, reaching 2.55 against 2.2 in 2016. The stark difference between the series throughout the distribution points toward a severe sample selection bias affecting the DLE estimates.

Figure 15: Aggregated markups, distribution



Notes: Aggregate markups in Italy, 2000-2016, estimated on CERVED data with θ^{Cerved}. Full sample (red), 90^{th} percentile of μ (green), 95^{th} percentile (navy) and 99^{th} percentile (cyan). Dashed lines refer to the average values of the limited firms per year in terms revenues (orange). Source: CADS (CERVED Group).

[25] DLE argue that the use of US-derived parameters was forced by the restricted sample that characterizes most of the countries in the sample (like Italy). However, CERVED data do not suffer from any sample size issue, and we are able to overcome such limitation.

6 The First Principal Component: a composite Indicator of Markup

In the previous sections, we presented several indicators of market power, resorting to both sectoral and firm-level data, and compared their features and dynamics, shedding light on the pros and cons of using one or the other measure. We further showed that, when estimated on a homogeneous sample, they ultimately return a quite univocal picture of the evolution of markups in Italy. Provided the need for robust and readily available measures of market power, to be used also for informing the competition policy decisions, in the present section, we propose a methodology to extract the informative content of the different metrics investigated so far.

To this aim, we conduct a principal component analysis (PCA) and choose the first principal component (PC1) as our composite indicator. In order to corroborate our proposed variable as a good proxy for markups, we propose an economic funded validation criterion and compute the correlation between the PC1 and other broadly accepted proxies of market power (namely: the Herfindahl–Hirschman concentration index, the concentration ratio, the market churn rate and the total factor productivity).

In the next subsection, we provide a theoretical foundation for the PC1 as synthetic measure of markups, describe its application on Italian data and present our validation strategy.

6.1 Conceptual Framework and Results

We conceptually state the problem of summarizing the information provided by index x_{it} as a signal extraction problem. We assume that each index conveys some information (signal) about a unique "true" markup measure y_t, although the information is carried with noise:

$$y_t = \alpha + \gamma x_{it} + \epsilon_{it}$$

where x_{it} indicates markup measure i at time t, y_t is the "true" value of markup at time t and ϵ_{it} are zero-mean noise terms. In econometric terms, the above equation can be interpreted as a factor model, where all observed variables are driven by a single factor (Barigozzi, 2018).

Thus, our proposed synthetic measure writes:

$$\hat{y_t} = PC_{1t}$$

where PC_{1t} is the first principal component computed from the singular value decomposition of the the $T \times L$ matrix of markup indices. As in case of averaging, the PCA gives rise to weighted sums of the noise terms ϵ_{it}, whose variance decreases as the cross-sectional dimension L increases (LLN); it explains the maximum variance in all the individual indicators (corresponding to the highest eigenvalue).

We compute our index for Italy, by employing multiple measures as our x_{it}, namely the Lerner markup, the DLEU and the DLW measures, then we conduct the PCA for the selected indices and select the first component as our proposed measure. Results are summarized in table 8: the first component explains more than half of the variance and its associated eigenvector, once normalized, provides the weights associated to each factor in the synthetic indicator. Thus, the DLEU and the Lerner measures both account for around 40 percent in the PC1, whereas the DLW index contributes for one fifth.

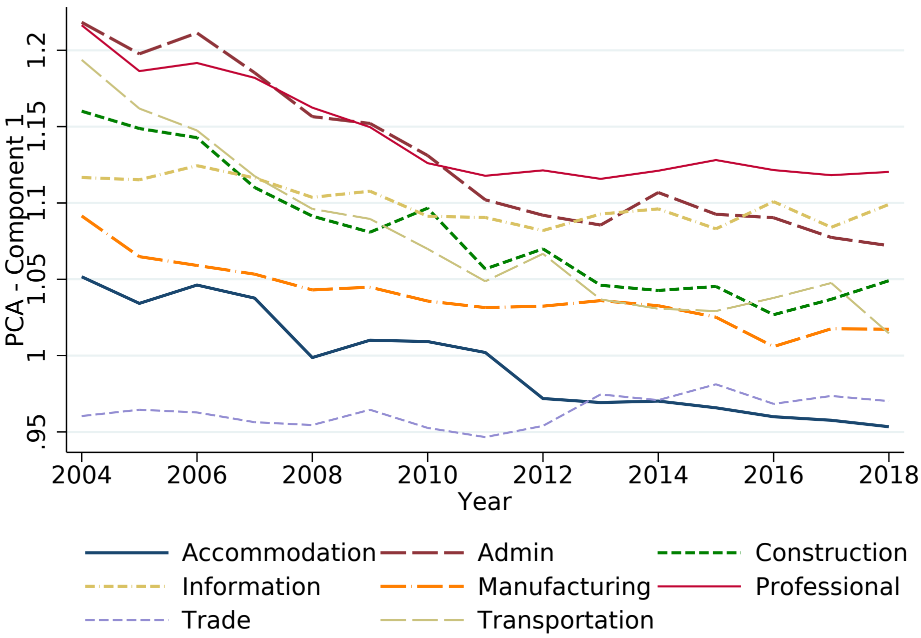
Table 8: PCA: Lerner, DLW and DLEU markup measures

	(1) Comp1	(2) Comp2	(3) Comp3
Eigenvalues	1.539	0.931	0.530
Variance proportion	0.513	0.310	0.177
Cumulative	0.513	0.823	1.00
Eigenvectors	0.644	-0.357	0.676
	0.357	0.922	0.147
	0.676	-0.147	-0.722

Notes: . Source: CADS, CERVED Group.

Figure 16 depicts the evolution of the PC1 indicator for the different sectors in the Italian economy throughout the last fifteen years. Our measure confirms the main findings presented in the previous sections: in Italy markups have evolved along a slightly decreasing pattern within the last 15 years, moving from 1.2 -in the total economy- in 2004 to 1.05 as of 2019 (last available data). The level has been higher in services -on average- rather than in manufacturing, though with a significant degree of heterogeneity among subsectors. In particular, professional services have shown the maximum value and the flattest dynamics, ranging between 1.21 at the beginning of our time span and 1.13 as of 2019; retail trade has displayed the lowest figures, while the steepest downwards trend has been featured by transportation.

Figure 16: PC1 markup measure by sector



Notes: . Source: CADS, CERVED Group.

In order to test whether our proposed variable is a good measure of markups, we introduce an economic funded validation criterion and compute the correlation between the PC1 and other indicators of market power, broadly used throughout the literature. In particularly we investigate the relation of our measure with two concentration indices (namely: the Herfindahl–Hirschman concentration index and the CR10 the concentration ratio of the first 10 firms in the market), a proxy for the degree of innovation among firms in their market (the total factor productivity) and an indicator of market dynamism (churn rate, computed as the sum of firms' entry and exit rate). Our results are summarized in table 9.

Table 9: PCA validation strategy

A) Component 1				
	(1) HHI	(2) CR10	(3) TFP	(4) Churn
γ	0.123*	0.215*	0.170***	-0.832***
	(0.0602)	(0.0849)	(0.0377)	(0.0766)
ρ	0.09	0.22	0.28	-0.33

B) Individual Components				
Lerner				
	(1) HHI	(2) CR10	(3) TFP	(4) Churn
γ	0.0681	0.119*	0.160***	-0.504***
	(0.0411)	(0.0580)	(0.0238)	(0.0561)
ρ	0.03	0.14	0.33	-0.26
DLW				
	(1) HHI	(2) CR10	(3) TFP	(4) Churn
γ	0.442**	0.671**	0.601***	-2.515***
	(0.162)	(0.230)	(0.0975)	(0.188)
ρ	0.22	0.30	0.44	-0.51
DLEU				
	(1) HHI	(2) CR10	(3) TFP	(4) Churn
γ	0.0128	0.0765	0.0505*	-0.265***
	(0.0365)	(0.0514)	(0.0237)	(0.0576)
ρ	0.08	0.07	0.06	-0.07

Notes: Validation exercise for *Component 1* of the PCA exercise (panel A). γ reports the estimated parameters in the regression of the HHI (column 1), the Concentration Ratio 10 (column 2), the TFP (column 3) and the Churn rate (column 4) against Component 1 of the PCA run across μ^{lerner}, μ^{DLW} and μ^{DLEU} (panel A) and all components taken individually (panel B). ρ reports the unconditional correlation coefficient. Source: CADS, CERVED Group.

In panel (a), the first line presents the estimated coefficient γ of a simple regression of PC1 on HHI (1), CR10 (2), TFP (3), and churn rate (4). As expected, the parameter is positive and statistically significant at the usual confidence level for the first three specification, indicating that higher markups are related - on average - to higher concentration and higher propensity to innovate, whereas the last coefficient is negative and significant, implying an inverse relation between market power and market dynamism (as higher entry and exit are generally associated to more competition). In the second line we report the correlation coefficient, whose values and signs confirm our validating criterion. In panel (b), we repeat the same exercise on the individual components of the PCA factor. The mixed results (e.g., not significant results for 2 out of 3 components when regressed against the HHI) confirm that our validation approach may prove useful in extracting further information by combining different markup measures.

7 Conclusions

In the context of the heated debate on the increased market power in the United States, particularly linked to the emergence of superstar firms, many contributions in the literature have investigated the evolution of markups, based mainly on macro and micro US data. However, the evidence for Europe is still scarce. The present work aims to fill this gap, proposing an analysis of the trends in markups for the major European countries, with particular attention to the Italian case. To this end, we have resorted to both macro and micro data and estimation techniques, namely reduced forms accounting measures (price-cost margins) and production function model-based indicators. According to our findings, markups in EU countries have followed divergent dynamics compared to the US: they have evolved along a flat/slightly decreasing pattern in the last decades, settling on average in level at 1.1 percent, against 1.6 in the US. Consistently, we did not find evidence of high concentration of market shares at the top of firms' distribution (no winner-the-most phenomenon seems to have occurred), whereas within sector/firm heterogeneity has proven the main determinant in driving markups evolution in the EU. Finally, we have proposed a composite measure of market power, the first principal component, summarizing the previously investigated indicators, and shown its effectiveness based on a set of validation variables.

Though our study is one of the few contributions focused on European data, many open question still remain to be addressed and further research would be needed. First, our cross-country analysis is partial, as it solely relies on sectoral data, while the micro-level measures are only constructed for the Italian case. This is partially due to data limitation, even if it could be partially overcome by employing the Orbis dataset. Secondly, most of the literature has been focusing on the consequences of rising market power as well as on the possible remedies to be adopted by competition Authorities. Much less attention has been devoted to the empirical investigation of the causes of specific markup dynamics, which could shed light on the different outcomes retrieved in the EU and in the US. Finally, as in the case of increasing markups, even the flat / decreasing trends conceal lights and shadows. On the one hand, it seems that the European institutional context favors the emergence of more competitive markets - probably thanks to a less restrictive regulation as well as to a more active role played by antitrust authorities (Gutiérrez and Philippon (2017, 2019)) - hence there should be less pressure downwards on wages and upwards on prices and inflation, as well as lower risks of reduced consumer welfare; on the other hand, the lack of emergence of large companies and the poor development of sectors on the technological frontier, such as digital and aerospace, could be associated with a production structure less prone to take up the challenge of innovation and therefore lead -in the medium term- to lose ground in terms of innovative capacity and productivity. In other words, if static efficiency seems to have been safeguarded so far, also probably thanks to the greater incisiveness of the European competition authorities, the implications in terms of dynamic efficiency should not be overlooked, especially in a post-pandemic recovery context such as the current one, in which Europe has huge resources to put to use to hopefully bridge the technological gap with the countries closest to the frontier, i.e. the US and China.

References

Ackerberg, Daniel A, Kevin Caves, and Garth Frazer. 2015. "Identification properties of recent production function estimators." *Econometrica*, 83(6): 2411–2451.

Antras, Pol, Teresa C Fort, and Felix Tintelnot. 2017. "The margins of global sourcing: Theory and evidence from us firms." *American Economic Review*, 107(9): 2514–64.

Atkeson, Andrew, and Ariel Burstein. 2008. "Pricing-to-market, trade costs, and international relative prices." *The American Economic Review*, 98(1995): 1998–2031.

Autor, David, David Dorn, Lawrence F Katz, Christina Patterson, and John Van Reenen. 2020. "The fall of the labor share and the rise of superstar firms." *The Quarterly Journal of Economics*, 135(2): 645–709.

Barigozzi, Matteo. 2018. "Dynamic factor models." London School of Economics and Political Science, Statistics Department, United Kingdom. Lecture notes.

Basu, Susanto. 2019. "Are Price-Cost Markups Rising in the United States? A Discussion of the Evidence." *Journal of Economic Perspectives*, 33(3): 3–22.

Bikker, Jacob A, and Katharina Haaf. 2002. "Competition, concentration and their relationship: An empirical analysis of the banking industry." *Journal of banking & finance*, 26(11): 2191–2214.

Boone, Jan. 2000. "Measuring product market competition." *CEPR Working Paper 2636.*

Caballero, Ricardo J, Emmanuel Farhi, and Pierre-Olivier Gourinchas. 2017. "The safe assets shortage conundrum." *Journal of Economic Perspectives*, 31(3): 29–46.

Calligaris, Sara, Chiara Criscuolo, and Luca Marcolin. 2018*a*. "Mark-ups in the digital era." *OECD Science, Technology and Industry Working Papers.*

Calligaris, Sara, Chiara Criscuolo, and Luca Marcolin. 2018*b*. "Mark-ups in the digital era." *OECD Science, Technology and Industry Working Papers.*

Christopoulou, Rebekka, and Philip Vermeulen. 2012. "Markups in the Euro area and the US over the period 1981–2004: a comparison of 50 sectors." *Empirical Economics*, 42(1): 53–77.

De Loecker, Jan, and Frederic Warzynski. 2012. "Markups and firm-level export status." *American economic review*, 102(6): 2437–71.

De Loecker, Jan, and Jan Eeckhout. 2018. "Global market power." National Bureau of Economic Research.

De Loecker, Jan, Jan Eeckhout, and Gabriel Unger. 2020. "The rise of market power and the macroeconomic implications." *The Quarterly Journal of Economics.*

Eggertsson, Gauti B, Jacob A Robbins, and Ella Getz Wold. 2018. "Kaldor and piketty's facts: The rise of monopoly power in the united states." National Bureau of Economic Research.

Gradzewicz, Michał, Jakub Mućk, et al. 2019. *Globalization and the fall of markups.* Narodowy Bank Polski.

Gutiérrez, Germán, and Thomas Philippon. 2017. "Declining Competition and Investment in the US." National Bureau of Economic Research.

Gutiérrez, Germán, and Thomas Philippon. 2019. "How EU markets became more competitive than US markets: A study of institutional drift." National Bureau of Economic Research.

Hall, Robert E. 1988. "The relation between price and marginal cost in US industry." *Journal of political Economy*, 96(5): 921–947.

Hall, Robert E. 2018. "New evidence on the markup of prices over marginal costs and the role of mega-firms in the us economy." National Bureau of Economic Research.

Haltiwanger, John C. 1998. "Measuring and analyzing aggregate fluctuations: the importance of building from micro-economic evidence." *Federal Reserve Bank of St. Louis Economic Review.*

IMF. 2019. "World Economic Outlook: Growth Slowdown, Precarious Recovery." IMF, Washington, DC.

Kim, Kyoo il, Yao Luo, and Yingjun Su. 2019. "A robust approach to estimating production functions: Replication of the ACF procedure." *Journal of Applied Econometrics*, 34(4): 612–619.

Koltay, Gabor, Szabolcs Lorincz, and Tommaso M Valletti. 2021. "Concentration and competition: Evidence from Europe and implications for policy." *Working Paper.*

Levinsohn, James, and Amil Petrin. 2003. "Estimating production functions using inputs to control for unobservables." *The review of economic studies*, 70(2): 317–341.

Loecker, Jan De, Catherine Fuss, and Johannes Van Biesebroeck. 2018. "Markup and price dynamics: linking micro to macro." *National Bank of Belgium, Working Paper*, , (357).

McAdam, Peter, Filippos Petroulakis, Isabel Vansteenkiste, Maria Chiara Cavalleri, Alice Eliet, and Ana Soares. 2019. "Concentration, market power and dynamism in the euro area." European Central Bank Working Paper Series 2253.

Raval, Devesh. 2020. "Testing the Production Approach to Markup Estimation." *Working Paper.*

Rizzica, Lucia, Giacomo Roma, and Gabriele Rovigatti. 2020. "The effects of shop opening hours deregulation: Evidence from Italy." *Working Paper.*

Roeger, Werner. 1995. "Can imperfect competition explain the difference between primal and dual productivity measures? Estimates for US manufacturing." *Journal of political Economy*, 103(2): 316–330.

Rovigatti, Gabriele, and Vincenzo Mollisi. 2018. "Theory and practice of total-factor productivity estimation: The control function approach using Stata." *The Stata Journal*, 18(3): 618–662.

Solow, Robert M. 1957. “Technical change and the aggregate production function.” *The review of Economics and Statistics*, 312–320.

Stiglitz, Joseph. 2015. *The great divide.* Penguin UK.

Syverson, Chad. 2019. “Macroeconomics and Market Power: Context, Implications, and Open Questions.” *Journal of Economic Perspectives*, 33(3): 23–43.

Thum-Thysen, Anna, and Erik Canton. 2015. “Estimation of service sector mark-ups determined by structural reform indicators.” Directorate General Economic and Financial Affairs (DG ECFIN) 547.

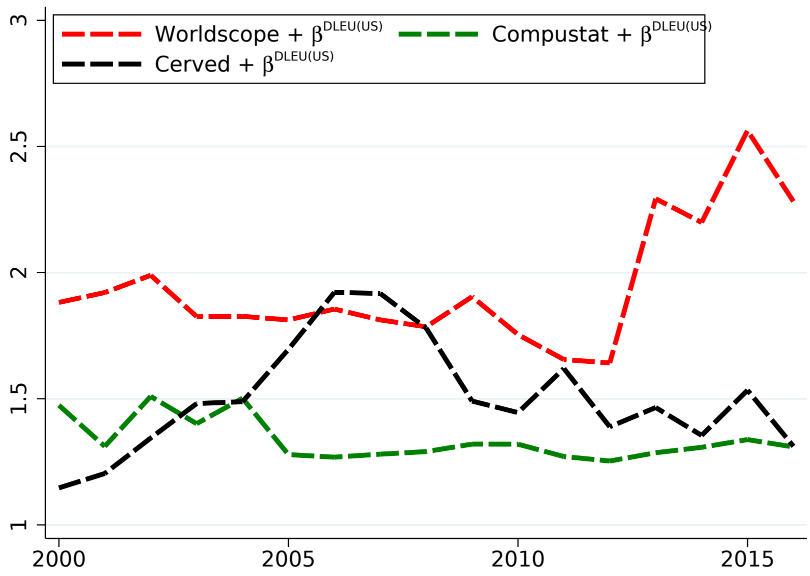
Traina, James. 2018. “Is Aggregate Market Power Increasing? Production Trends Using Financial Statements.” *Working Paper.*

A Additional Figures and Tables

Figure AA.1: De Loecker and Eeckhout (2018) Italian markup series, 1980-2016

Notes: Aggregate markups 1980-2015, Italy. Source: Worldscope, taken from De Loecker and Eeckhout (2018).

Figure AA.2: Replica of De Loecker and Eeckhout (2018) Italian markup series with Worldscope, Compustat, and Cerved



Notes: .

B Micro Markups - Sector Data

Table BB.1: Importance of incorporated firms

	Firms	Workers	Value added
Manufacturing	51.5	81.6	91.0
Utilities	73.1	87.4	95.9
Construction	46.7	63.7	71.7
Trade	41.1	65.5	78.9
Transport and Storage	46.7	63.3	80.9
Accomodation and Restaurant	28.6	45.6	58.0
Information and communication	73.9	87.4	90.0
Professional Services	30.8	53.9	59.4
Other Business Services	47.2	73.0	80.6

Notes: The table shows the relevance of incorporated firms in term of number of firms (first column), the share of workers (second column) and the share of value added (third column). All computations are done relative to the universe of firms with at least 1 paid employee.

Figure BB.1: Percentiles of the markup distribution in service sectors

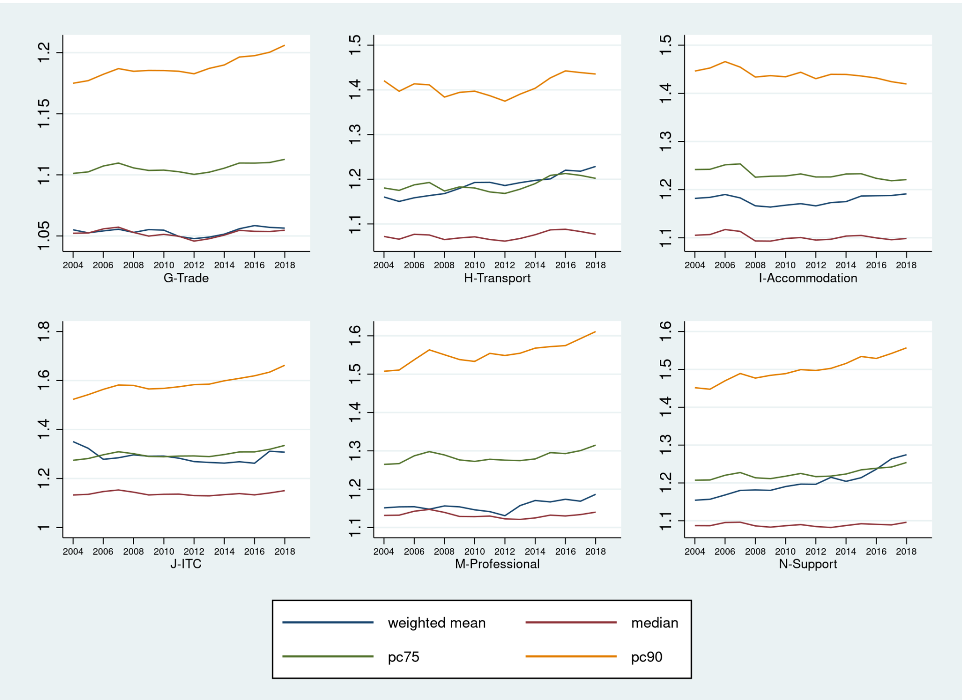


Figure BB.2: Decomposition of markup dynamics in services sectors

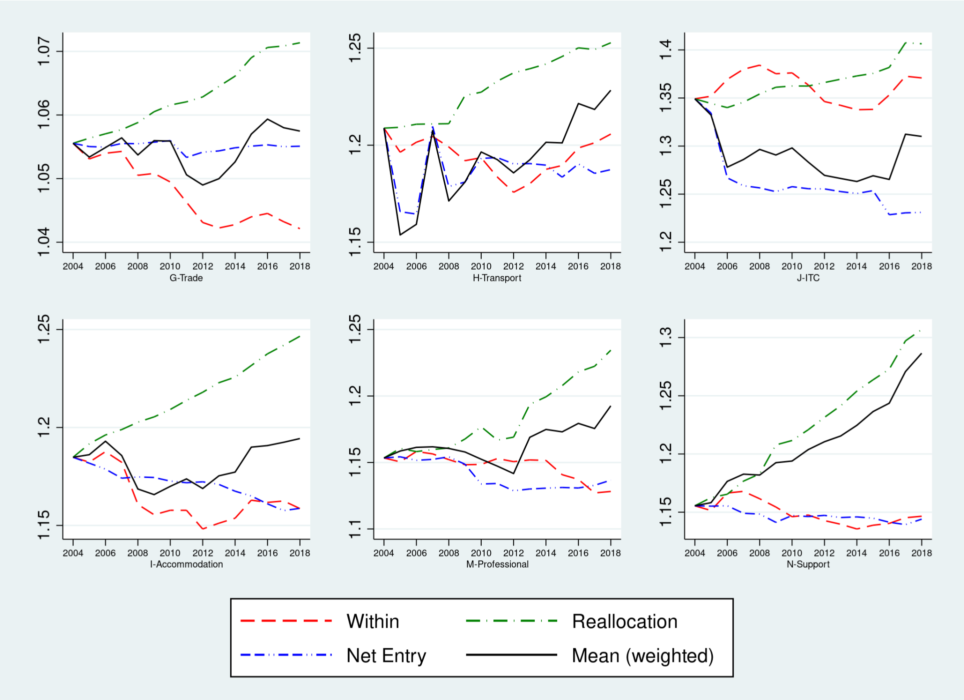


Figure BB.3: DLW Markups by branch of activity - index, 1995 base year

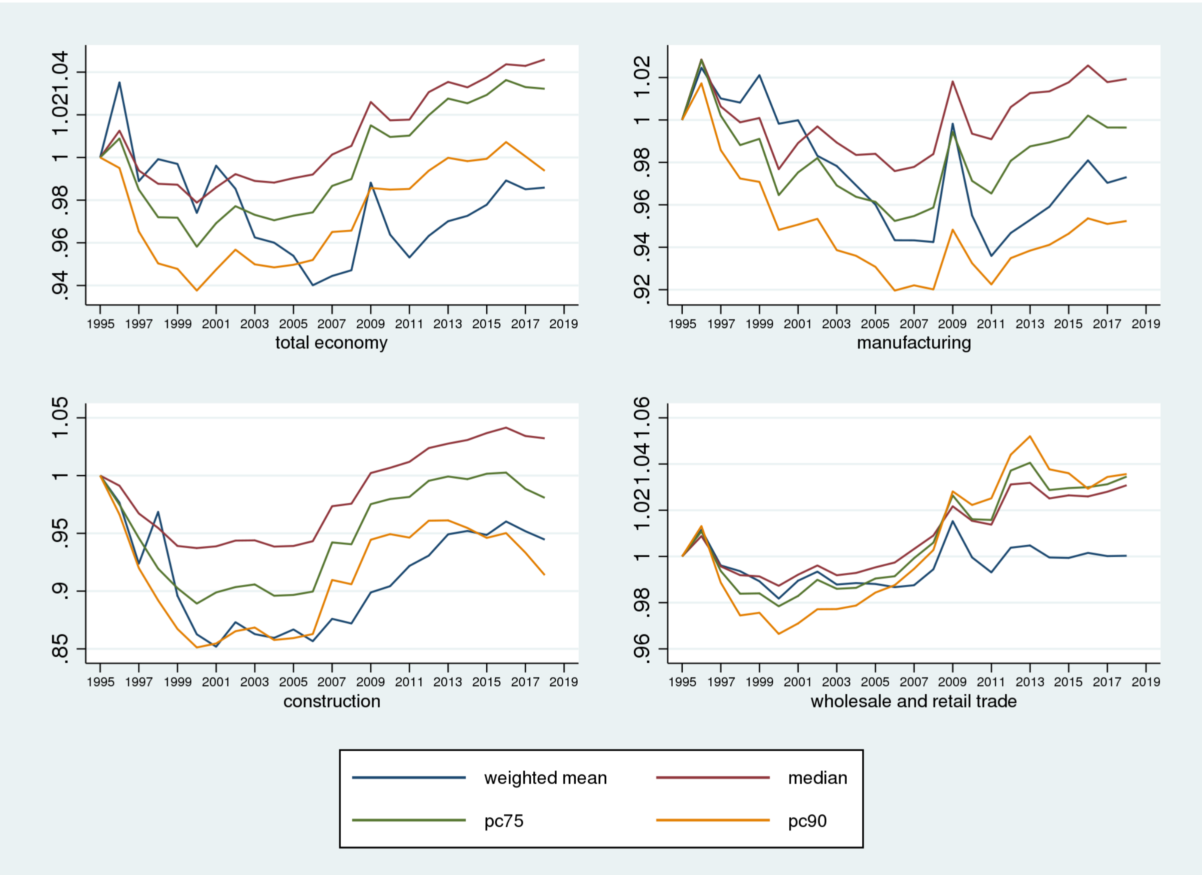
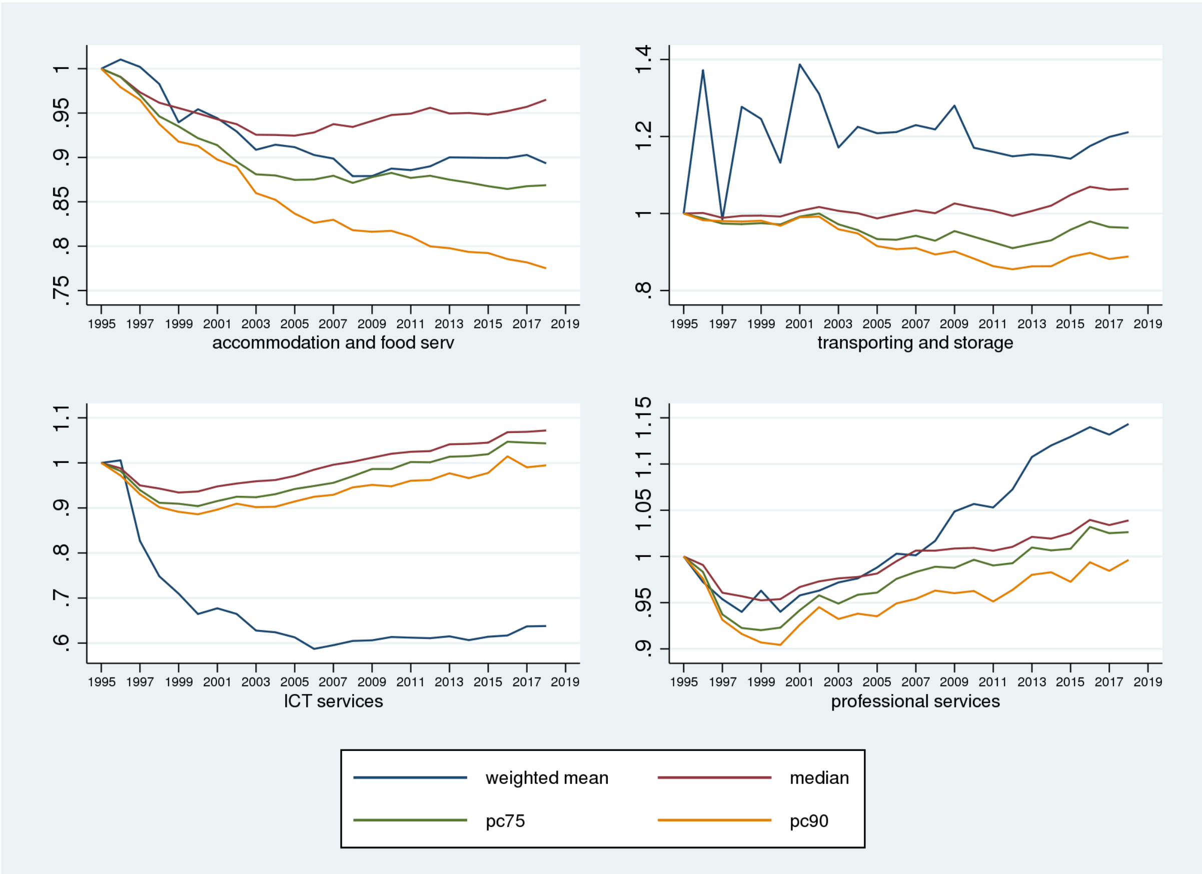


Figure BB.4: DLW Markups by branch of activity - index, 1995 base year



C Theoretical Background

The general framework The analysis and discussion in the next session of the paper rest on the following theoretical background: let's consider an oligopoly á la Cournot within an industry with N heterogeneous firms. At each point in time, all single-product firms maximize the profit function

$$\Pi_{it} = p_{it}x_{it} - c_{it}\left(x_{it}\right) - F_{it}$$

where p_{it} and x_{it} are output price and quantity, respectively, $c(\cdot)$ is the cost function, and F_{it} stands for a firm-specific amount of fixed costs of production. By inverting the demand function, it is possible to retrieve the equilibrium price level[26]

$$p^{*} = p\left(X_{it}\right) = p\left(x_{1t} + x_{2t} + ... + x_{Nt}\right)$$

As a result, each firm i solves

$$\max_{x_i}\left[p\left(X_{it}\right)x_i - c_i\left(x_i\right) - F_i\right] \tag{7}$$

The Lerner Index, Markup and the Modified Lerner A first measure of murkups is given by a function of the Price-Cost margin (or *Lerner Index*, L). In formulas:

$$L_{it} = \frac{P_{it} - MC_{it}}{P_{it}}$$

where i stands for the chosen panel variable (i.e., firm, sector, country, etc.) and t for the time variable; P is the *price* and MC the marginal costs.[27]

Turning to a monopoly model, following the FOC, we obtain:

$$L_{it} = -\frac{1}{\varepsilon_{it}}$$

where ε_{it} is the price elasticity of demand, and therefore:

$$L_{it} \rightarrow \begin{cases} 0 & \varepsilon_{it} \rightarrow \infty \\ \\ 1 & \varepsilon_{it} \rightarrow -1 \end{cases}$$

The Lerner index is easily measurable, varies in time, and has straightforward interpretations at the firm level; on top of that, is computable at the individual as well as at the aggregate level. The macro analysis that follows (section 3) is based on the sector-level Lerner index ($L_{jt} = \frac{P_{jt}-MC_{jt}}{P_{jt}} = \frac{\sum_{i\in j} P_{it}-MC_{it}}{\sum_{i\in j} P_{it}}$). For both the micro and the macro indices, given the lack of reliable measures of marginal costs, we have to proxy MC_{it} with the total variable costs - either retrieved in balance-sheet data, or on the National Accounts. Hence, we compute the measure $\hat{L}_{jt} = \frac{GOM_{jt}}{Y_{jt}}$, which is the ratio between the Gross Operating Margin, [28] and the total output Y.

[26] For the sake of simplicity, we omit the subscript t.
[27] In the empirical analysis, we proxy marginal costs with average costs, see below.
[28] The Gross Operating Margin amounts to the total revenues minus the total variable costs.

Finally, in order to compute the markups we use the monotone transformation:

$$\mu_{it}^{Lerner} = \frac{1}{(1 - \hat{L}_{it})}$$

Pros and Cons The Lerner based measure of markup has two main advantages. First of all, it is possible to compute it at both the macro (National Accounts) and micro (firm data) levels, and allows for a comparison of the two measures; second, being an accounting measure, it is less prone to estimation errors and measurement issues. Among the latter, the main source of bias in the micro data is represented by the measurement of production factors - e.g., due to underestimation of the size of self-employment. Despite our efforts to account for all the possible sources of bias in the macro analysis - see below - there is less room for corrections on firm-level data.

Hall (JPE, 1988) and Roeger (JPE, 1995) framework Under the assumptions of Constant Returns to Scale (CRS) and Hicks neutral technological changes, the latter are captured by the Solow (1957) residuals (SR), in the context of profit maximization problems.[29] Hall (1988) shows that, in case of imperfect competition, the SR do not nail down the technological change θ anymore. What they reflect is, instead, a weighted sum of θ and the growth rate of the output-capital ratio - where the weights are a function of the markups. Hence, following the profit maximization problem, the quantity-based SR read

$$\begin{aligned} SR_t = \Delta Q_t - \alpha_{N_t}\Delta N_t - \alpha_{M_t}\Delta M_t - (1 - \alpha_{N_t} - \alpha_{M_t})\Delta K_t = \\ = \left(1 - \frac{1}{\mu_t}\right)(\Delta Q_t - \Delta K_t) + \left(\frac{1}{\mu_t}\right)\theta_t \end{aligned} \tag{8}$$

where ΔX_t is the growth rate of X, α_J are factors' shares, and μ_t is the price-cost markup. In order to correctly estimate (8), In order to correct for endogeneity and to to ensure unbiased estimates of μ_t, Hall proposes to use unexpected growth in military spending as exogenous demand shifters.

Building on the above results, Roeger (1995) proposes to exploit the dual of problem (8), based on cost minimization, to obtain price-based SR (SRP). More specifically, the equation reads

$$\begin{aligned} -SRP_t = \Delta p_t - \alpha_{Nt}\Delta w_t - \alpha_{Mt}\Delta m_t - (1 - \alpha_{Nt} - \alpha_{Mt})\Delta r_t \\ = \left(1 - \frac{1}{\mu_t}\right)(\Delta p_t - \Delta r_t) - \left(\frac{1}{\mu_t}\right)\theta_t \end{aligned} \tag{9}$$

where Δp and Δw stand for price and wage changes, respectively, while Δm and Δr capture the adjustments in input prices and interest rate. Under perfect competition, equations 9 and 8 should yield the same amount, net of markups and with opposite signs. The main intuition behind Roeger method is that, by summing up the the quantity-based and the price-based SR, the technological changes are net

[29] We borrow the notation used in this section from Christopoulou and Vermeulen (2012).

out of the equation, and the resulting terms are all nominal (observable) variables

$$\underbrace{(\Delta p_t + \Delta Q_t)}_{Output\,growth} - \alpha_{N_t} \underbrace{(\Delta w_t + \Delta N_t)}_{labour\,cost\,growth} - \alpha_{M_t} \underbrace{(\Delta m_t + \Delta M_t)}_{Input\,cost\,growth} - (1 - \alpha_{N_t} - \alpha_{M_t}) \underbrace{(\Delta r_t + \Delta K_t)}_{Capital\,cost\,growth} =$$

$$\underbrace{SR_t - SRP_t}_{y_t} = \underbrace{\left(1 - \frac{1}{\mu_t^{Roeger}}\right)}_{\beta} \underbrace{[(\Delta p_t + \Delta Q_t) - (\Delta r_t + \Delta K t)]}_{x_t} \tag{10}$$

where, for estimation purposes, μ_t is constant and the relative estimating equation reads $y_t = \beta x_t + \epsilon_t$. The linear regression of y_t on x_t yields a consistent estimate of β - which can be inverted to obtain $\hat{\mu}^{Roeger} = \frac{1}{1-\hat{\beta}}$.

Pros and Cons the Roeger method has several advantages with respect to alternative approaches to aggregated markup estimation. First, it is relatively easy to gather the data needed for the estimation;[30] moreover, it allows for robust comparisons across countries and sectors. On the other hand, there are two major drawbacks, as it i) yields a time-invariant markup measure, and ii) assumes CRS. In order to tackle the former issue, there are slightly modified versions of equation (10) which - by including time-varying indicators for structural reforms (i.e., Product Market Regulation indices) or time trends - yield time-varying estimates of μ^{Roeger}.

De Loecker and Warzynski (AER, 2012) framework De Loecker and Warzynski (DLW, henceforth) propose to exploit a dual problem similar to Roeger's, but they focus on individual firms, and assume a Hicks-neutral productivity term and, for identification purposes, common technology parameters.[31] The general-form production function $Y_{it} = Q_{it}(X^1_{it}, ..., X^V, K_{it}, \omega_{it})$ requires V *variable inputs* (X^v), firm's capital stock K_{it} and the idiosyncratic technology parameter ω_{it}.[32]

The cost-minimizing firms face a problem whose associated Lagrangian function reads

$$\mathbb{L}(X_{it}, K_{it}, \lambda_{it}) = \sum_{v=1}^{V} P_{it}^{X^v} X_{it}^v + r_{it} K_{it} + \lambda_{it}(Y_{it} - Q_{it}(\cdot)) \tag{11}$$

where $P_{it}^{X^v}$ stands for the v^{th} variable input price, and r is capital K cost. For the sake of simplicity - and without loss of generality - in what follows we assume a single-input (X_{it}) production technology. The first-order condition with respect to the variable input, net of input prices, is

$$\frac{\partial \mathbb{L}}{\partial X_{it}} \Rightarrow P_{it}^X - \lambda \frac{\partial Q_{it}(\cdot)}{\partial X_{it}} = 0 \underbrace{\Longrightarrow}_{\frac{X_{it}}{Y_{it}}} \frac{\partial Q_{it}(\cdot)}{\partial X_{it}} \frac{X_{it}}{Y_{it}} = \frac{1}{\lambda_{it}} \frac{P_{it}^X X_{it}}{Y_{it}} \tag{12}$$

where the shadow price $\lambda_{it} = \frac{\partial \mathbb{L}_{it}}{\partial Y_{it}}$ is the marginal cost of production. According to equation (12), then, the optimal input demand requires the firm to equalize the output elasticity of (any) variable input

[30] The National Accounts are made available by EUROStat, EU KLEMS, and several National Statistical offices, on top of international organizations like the OECD. Data on capital costs can be retrieved, for EU members and a few other countries, in the AMECO database, using investment deflators and long-term interest rate data - see below.

[31] For Cobb-Douglas production functions, this assumption translates into common output elasticities, too. For alternative specifications of production functions (e.g., translog), though, that is not necessarily the case.

[32] Variable inputs proposed in the literature include skilled/unskilled labor, electricity, intermediate input and raw materials.

X_{it} - the left-hand side - to the equation right-hand side.

Following the above discussion, we define the markup as the ratio between input prices and marginal production cost, i.e., $\mu_{it}^{DLW} \equiv \frac{P_{it}}{\lambda_{it}}$, and we substitute the definition back into equation (12) to yield

$$\theta_{it}^{X} = \mu_{it}^{DLW} \frac{P_{it}^{X} X_{it}}{P_{it} Q_{it}} \tag{13}$$

where $\theta_{it}^{X} = \frac{\partial Q_{it}(\cdot)}{\partial X_{it}} \frac{X_{it}}{Y_{it}}$ is the output elasticity of input X. Rearranging equation (13), and defining the input share of X on total outcome as $\alpha_{it}^{X} = \frac{P_{it}^{X} X_{it}}{P_{it} Q_{it}}$, the straightforward formula for markup estimation reads

$$\mu_{it}^{DLW} = \frac{\theta_{it}^{X}}{\alpha_{it}^{X}} \tag{14}$$

While the values of α_{it}^{X} can be found in the data - being the share of input costs on total firm output, with a caveat that we explain below - the estimation of θ_{it}^{X} requires to estimate $Q(\cdot)$ at the firm level. In particular, De Loecker and Warzynski (2012) propose to use a flexible, yet relatively parsimonious in terms of data requirements method: they rely on a (log) translog production function, with second-order polynomial in variable and dynamic inputs. In the estimation, they implement the estimation procedures originally proposed by Levinsohn and Petrin (2003), as modified by Ackerberg, Caves and Frazer (2015). More specifically, the value added translog function is given by

$$\begin{aligned} y_{it} &= \beta_l l_{it} + \beta_k k_{it} + \beta_{ll} l_{it}^2 + \beta_{kk} k_{it}^2 + \beta_{lk} l_{it} k_{it} + \omega_{it} + \varepsilon_{it} = \\ &= \phi_{it}(l_{it}, k_{it}, m_{it}, \boldsymbol{z_{it}}) + \varepsilon_{it} \end{aligned} \tag{15}$$

with m_{it} being intermediate input cost and $\boldsymbol{z_{it}}$ a suitable instrument for the productivity term (that is, the lagged values of the variable input). Through the first-stage estimation, it is possible to retrieve an estimate of ε. Then, exploiting the markovian nature of the productivity law of motion, the second-stage estimation yields $\hat{\beta} = (\beta_l, \beta_k, \beta_{ll}, \beta_{kk}, \beta_{lk})$. The output elasticity to labor input, according to (14), reads

$$\theta_{it}^{l} = \hat{\beta}_l + 2\hat{\beta}_{ll} l_{it} + \hat{\beta}_{lk} k_{it} \tag{16}$$

Finally, the observed expenditure share $\tilde{\alpha}_{it}^{l} = \frac{P_{it}^{l} l_{it}}{P_{it} \tilde{Y}_{it}}$ is biased - that is, the observed output $\tilde{Y}_{it}$ includes the first-stage residuals, i.e., $\tilde{Y}_{it} = Y_{it} \exp(\varepsilon_{it})$. Given the fitted residuals computed in (15), the estimable, correct version of markups is

$$\alpha_{it}^{l} = \frac{P_{it}^{l} l_{it}}{P_{it} \frac{\tilde{Y}_{it}}{\exp(\hat{\varepsilon}_{it})}} \tag{17}$$

Pros and Cons the DLW method is very appealing, because it allows for firm-level, time-varying estimates, without the need to assume constant returns to scale. Although the indisputable advantages, there are data issues that countervail some of the benefits. First and foremost, DLW method requires the estimation of the production function, with all the associate empirical drawbacks - see (Raval, 2020; Rovigatti and Mollisi, 2018; Kim, Luo and Su, 2019) for recent contributions on the topic. Second, and related, in most cases the firm-level data suffer from measurement errors that are hard to correct, do not include expenses on intangibles, and are selected on measures like size, revenues, or profitability. Finally, the aggregation at the sector/overall economy relies on arbitrary weighting, whose choice informs the results.

De Loecker, Eeckhout and Unger (QJE, 2020) In a very recent contribution, De Loecker, Eeckhout and Unger (DLEU) propose a slightly modified version of the DLW markup estimation framework to accommodate a few empirical drawbacks related to the dataset that they employ and to the time span that they consider. First, in their main specification they estimate the production function using as control a variable input in production (the *Cost of Good Sold* variable, or COGS), which contains both costs related to the production as well as costs that are generally considered fixed - e.g., factory overhead costs or, depending on the dataset used, a measure of direct labor employed in production.[33] Finally, to avoid possible under- or over-estimation of the elasticity due to unobservable dynamics of the technology parameter, they estimate a time-varying version of the production function, which allows for further flexibility in the within-sector parameter estimation.

Concentration Measures and Testable Relations Throughout the paper, we proxy the concentration with two widely-used measures: the Herfindal-Hirschman Index (HHI) and the K-Concentration Ratio. The former reads $HHI_{jt} = \sum_{i=1}^{N_j} s_{i,jt}^2$, where s_{ijt} stands for the market share of firm i, in sector j at time t; the latter is the sum of the market shares of the biggest K firms in sector j at time t, that is $CR_{jt}^k = \sum_{i=1}^{N_j} s_i$.

Pros and Cons Concentration measures are used in most of the relevant academic literature as well as by regulators, authorities, and policymakers - e.g. among many others, antitrust authorities set precise thresholds on both the level of HHI to assess whether a market needs further scrutiny due to excessive concentration, and on the changes in HHI to assess post-merger effects. Their success is due to their computational simplicity, as the amount of revenues *per firm* in the market is all of what is needed, and to their comparability across time, sectors, and countries.

There are, however, a few major drawbacks which

High levels of concentration, though, are not sufficient conditions for lack of competition. In particular, they might indicate markets subject to high levels of turnover (entry, exit and relocations, (Bikker and Haaf, 2002; Boone, 2000)), or might be due to efficiency differences among firms. Finally, either the dynamics/evolution of the markets, or an improper definition of relevant market itself could bias the observed level of concentration.

Relations to be tested Following simple algebraic steps,[34] we predict a few relations between concentration measures, markups and price-cost margins that we will be able to empirically test on real data. Indeed, provided that the very mild assumptions underlying our model hold, i) the price-cost margin should be positively correlated with the concentration; ii) the price-cost margin, as well as the concentration measures, should be positively correlated with the average *technical efficiency* (that we proxy with with the total factor productivity, TFP).

[33] See the discussions in Traina (2018) as well as in the original De Loecker, Eeckhout and Unger (2020) paper which directly address this point.

[34] See the Technical Appendix.