Global Declining Competition?*

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Abstract

Using a new firm-level dataset on private and listed firms from advanced economies and emerging markets, we document four stylized facts on market power in global markets. First, competition has declined, but only modestly—average markups increased from 1.22 to 1.29 (6%) during 2000–2015, especially in services and in advanced economies. Second, the markups of listed firms are higher and experienced stronger increases than those of private firms. Third, the markup increase is driven by firms in the top decile of the markup distribution (which includes both large and small firms), and there is a U-shaped relation between firm size and markups. Finally, the increase is mostly driven by increases within incumbents and, to a lesser extent, by market share reallocation towards high-markup entrants.

JEL: D2, D4, E2, F6, L1, L4
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1 Overview

Market power is back at the center of policy and academic discussions. Indeed, there is widespread concern that the world economy may be entering a new Gilded Age, characterized by a decline in competition and the rise of monopolies that generate resource misallocation, inequality, and welfare losses. On the academic front, much of the discussion was spurred by recent work that documented a sharp decline in competition in the United States and linked it to several macroeconomic phenomena affecting the U.S. economy like the decline in the labor share, low investment, and the reduction in new business formation—see Council of Economic Advisers (2016), Gutiérrez and Philippon (2017), and De Loecker et al. (2020).

In this paper we present new evidence on market power providing an assessment of the evolution of competition in the global economy during the period 2000-2015. Specifically, we compute markups for publicly listed and *privately* held firms from a set of advanced and emerging countries accounting for roughly 70% of world GDP.[1] Contrary to previous studies based on just listed firms, we only find a modest increase in average markups, which stresses the importance of considering the full firm distribution for properly understanding the recent dynamics of competition in the global economy. To the best of our knowledge, ours is in fact the first study focusing on the contribution of both private and listed firms to the evolution of aggregate markups in a sample of developed and emerging countries.[2]

In particular, we document the following stylized facts that we further develop in the rest of the paper:

(**F1**) Global markups increased from 1.22 to 1.29 (6%) between 2000 and 2015; this increase is concentrated in *service sectors* and in *advanced economies*.

(**F2**) Markups of *listed* firms are higher and experienced a stronger increase than markups of private firms.

[1] Throughout the paper, and as is traditionally the case in the literature, we link markups to market power; in Section 2 we discuss this issue as well as alternative measures of market power. In addition, the papers presented at the Summer 2019 *Journal of Economic Perspectives'* symposium on markups provide an excellent review on the subject.

[2] De Loecker and Eeckhout (2020) and Díez et al. (2018) also compute global market power measures based on large sets of countries. However, they use data only on publicly listed firms. De Loecker et al. (2020) provide markup estimates from listed and privately held firms but focus only on the U.S. economy. Calligaris et al. (2018) compute markups for a sample similar to ours but focus on the digital economy.

(**F3**) The increase is driven by the *top decile* of the markup distribution, composed by large and small firms; and there is a *U-shaped* relation between firm size and markups.

(**F4**) The increase in markups is mostly explained by *within*-firm increases among incumbents and, to a lower extent, by market share *reallocation* towards high-markup entrants.[3]

We can further characterize our main findings as follows. First, we document a modest decline in global competition, measured by an increase in average markups of 6% between 2000 and 2015. This average increase, however, masks great heterogeneity at different levels. For instance, we document stark differences across countries, with markups increasing among advanced economies but not as much among emerging markets. Differences across sectors are even more significant, with markups in service sectors increasing faster than in manufacturing. Further, we also document that the markups of listed firms are larger and increased faster than that of private firms, and this pattern holds for the overall sample and when looking by sector or country. Motivated by this finding, we rank firms according to their average markup and explore the evolution of different moments of the markup distribution. The aggregate markup increase is mostly explained by the behavior of a small fraction of high-markup firms (the top decile of the markup distribution), whose markups increased 40 percent, in contrast to firms in the bottom half of the markup distribution that show stagnant markups—both facts translate into a significant increase in markup dispersion. Furthermore, these high-markup firms are spread economy-wide across all sectors (although they are more likely to be found in sectors that use digital technologies more intensively), implying substantial within-sector markup heterogeneity. Most importantly, high-markup firms include both large and small firms as well as listed and private firms. Taken together these facts suggest that to study markups relying just on listed firms can be misleading as the mass of firms ignored is not just concentrated on one tail of the distribution but, rather, it is spread throughout the entire distribution of markups—including the crucial right tail driving markup dynamics.

Given the importance of high-markup firms in the evolution of global markups, we next explore in detail the relation between firm size and markups to assess their quantitative importance. Contrary to common wisdom, we find that, unconditionally, smaller firms have higher markups

[3] This finding holds for the overall sample. In the case of the U.S., however, we find that most of the increase in markups is actually explained by the reallocation effect, that is, by high-markup firms becoming relatively larger, something in line with the findings on superstar firms by Autor et al. (2020).

even within narrowly defined industries—only when we focus on very large firms do we find a positive relation. However, conditional on firm observable characteristics, we find a non-monotonic (U-shaped) relationship between firm size and markups both in the cross-section and in the within-firm time variation, reconciling with the fact, also found in previous studies based on listed firms only, that the largest firms tend to have higher markups. Both findings unveil a new stylized fact: markups first decrease with firm size and only when a (fairly large) size threshold is reached, markups start increasing with firm size. In line with this finding, we show that the group of high-markup firms includes large firms but is also composed of rather small firms—these are likely firms operating in niche markets, facing inelastic demands that allow them to charge high markups.

To assess the relative importance of different drivers in the overall markup increase (i.e., changes within vs reallocation across firms), we conduct a decomposition *à la* Melitz and Polanec (2015). We find that most of the aggregate increase in markups is driven by within-firm increases of incumbent firms and, to a smaller degree, by successful new high-markup firms. Once again, we find somewhat different results when we focus on listed firms, for which the market share reallocation effect among incumbent firms and new entrants play a sizable role—something in line with previous findings for the U.S. (Baqaee and Farhi (2019)).

Finally, the paper shows that the main results are robust to different production function specifications and estimation techniques. Specifically, we find that the moderate increase in markups is also observed if we use a rolling-window estimation to allow for time-varying elasticities or if we estimate a translog production function (instead of the baseline Cobb-Douglas). In addition, we document the robustness of the results to a setup that considers the role of overhead costs and to markup computations that do not rely on production function estimation (the so-called cost share approach).

The paper is related to a burgeoning literature on firms' market power and its macroeconomic effects. De Loecker et al. (2020) estimate a sharp increase of U.S. markups, and link it to several macroeconomic phenomena, including declines in the labor share, the labor participation rate, and aggregate output growth. Hall (2018) provides evidence of heterogeneous increases in market power in U.S. industries and some evidence that growth of high-markup mega-firms is associated with rising market power in the United States. Gutiérrez and Philippon (2017) document a significant increase in market power by firms in the U.S. (measured as higher concentration rates) and how this has negative macroeconomic consequences like, for instance, lower investment. Díez et al. (2018), using data on listed firms, document an increase in global markups and find evidence of a non-monotonic (inverted U-shaped) relation between markups and investment with a sizable fraction of firms currently located at markup levels such that further increases are associated with lower investment rates. The documented increased in firm level markups, especially based on U.S. listed firms, spurred a renewed interest on the potential aggregate effects of such increases. For instance, Baqaee and Farhi (2019) develop a model for aggregating microeconomic shocks and find that the elimination of markups in the U.S. would increase total factor productivity (TFP) by 20 percent. Edmond et al. (2018) calibrate a model and estimate the different costs of markups, finding that the main costs are the aggregate markup acting as a tax on output and the generated misallocation of inputs.[4] Another strand of the literature focused on the driving forces behind the aggregate markup increases. For instance, differences in the institutional setting have been proposed as a potential source of the observed declined in competition with important implications for productivity growth. Gutiérrez and Philippon (2018) document lower concentration measures in European markets compared to the U.S. and provide evidence on differences in the independence of antitrust authorities to rationalize their findings. Akcigit et al. (2018), focusing on Italy, show that market leaders are more likely to be politically connected, which in turn translates into higher rates of survival, growth in employment and revenue, but interestingly, not in higher productivity or innovation. Van Reenen (2018) provides an overview of alternative explanations to differences in antitrust enforcement, namely, globalization and technological change, to explain the observed increase in market power. Yet another series of papers have raised some methodological concerns with the estimation approach by De Loecker et al. (2020) that has been at the forefront of this literature. Traina (2018) and Karabarbounis and Neiman (2018) find smaller markup increases after controlling for all variable inputs; Bond et al. (2020) stress the difficulties of properly estimating output elasticities that, in turn, are needed for markup estimation. Both Basu (2019) and Syverson (2019) provide comprehensive reviews on different firm level markup estimation approaches, the implicit assumptions as well as the aggregate implications.

[4] Other related work includes Barkai (2020) that estimates a rise in the aggregate markup for the U.S. private sector while explaining the decline in the labor and capital shares. Eggertsson et al. (2018) develop a model to explain how increased market power together with a decreased natural rate of interest can explain recent puzzling macroeconomic facts, including an increase in Tobin's Q permanently above 1, a decrease in the ratio of investment to output, and declines in the labor and capital shares.

We contribute to this literature in several aspects. First, we highlight the importance of looking at the entire distribution of firms, including privately-held ones, to properly assess the actual level of competition in a market and, most importantly, its macroeconomic relevance and implications. In contrast, most of the literature focuses on publicly listed firms thereby missing sizable portions of the firm distribution. Using the same methodology that is standard in the literature, we find an overall markup increase significantly lower than studies based only on listed firms precisely due to the presence of private firms. At the same time, our results show that the increase in markups is driven by high-markup firms which include both listed and private firms—it follows that looking to both types of firms is critical to understand the economy-wide macroeconomic implications. Second, most of the attention thus far has been concentrated on U.S. listed firms while our analysis is based on a broad cross-country coverage, including emerging markets.[5] Third, we document that differences across sectors are more prevalent than across countries and highlight the significant contribution of the service sectors to the evolution of aggregate markups during the last two decades. Forth, we also contribute to the literature by unveiling the non-monotonic (U-shaped) relationship between markups and firm size, a previously unknown stylized fact. Finally, our breakdown between the different sources of markup increase (i.e., within vs reallocation), and the differences between regions, contributes to the understanding of recent firm dynamics in the U.S. *vis-à-vis* Europe and provides information that could be used in the design of the appropriate policy responses.

The rest of the paper is organized as follows. In Section 2 we discuss the methodological issues around market power and markup estimation. In Section 3 we describe our dataset. In Section 4 we present our baseline results on global market power. Section 5 documents the link between market power and size. Section 6 conducts the decomposition of the markup increase. Section 7 presents the robustness analysis of our markup estimations. Finally, Section 8 concludes.

[5]One early study extending the analysis to European countries is Gutiérrez and Philippon (2017). Recently, Díez et al. (2018), De Loecker and Eeckhout (2020) and Karabarbounis and Neiman (2018) have provided additional evidence on *listed* companies for a wider set of countries.

2 Measuring Market Power

Measuring the existence and degree of market power is usually extremely hard. Industry concentration is the most commonly used measure, partly because it is the easiest to construct once a market is properly defined (which could be daunting by itself). Previous work has documented an increase in industry concentration in the U.S. (see Furman and Orszag (2018); Grullon et al. (2019); Autor et al. (2020)) while the evidence for other geographical areas is mixed (see Gutiérrez and Philippon (2018), Kalemli-Özcan et al. (2015) and Bajgar et al. (2019)). However, an increase in industry concentration can be suggestive of a decline in competition but it could also reflect competition at work, where more efficient firms are able to gain market share (Shapiro (2018), Basu (2019), Syverson (2019)). Further, even a fully concentrated industry may not behave uncompetitively if markets remain contestable, as suggested by Baumol (1982). Thus, by themselves, concentration measures provide an incomplete characterization of the degree of competition.

Consequently, emphasis has been placed on an alternative firm-level measure of market power, the so-called markup, that measures the gap of price over marginal cost—this is the approach followed in the paper and is, in fact, the textbook definition of market power (see Tirole (1988)). Still, the link between market power and markups may not be one-to-one in the presence of fixed costs, as firms pricing above marginal costs could be just recouping non-operational costs. However, as we discuss below, our markup results carry through even after controlling for overhead costs. Finally, the existence of extraordinary profits can also be seen as evidence of the existence of market power. The empirical evidence suggests that increases in firm markups are also associated with increases in profits beyond any potential increase in overhead costs (see De Loecker et al. (2020))—and while our data on profitability is limited (we do not observe dividends, for instance) we are able to document an increase in operating margins and to link it to the increase in markups.

While the definition of markups is a very clear economic concept, its estimation is not as straightforward. The reason is that firm prices and marginal costs are two variables that are often not observable in most firm-level databases. Rather than focusing on the demand side to estimate markups, Hall (1986, 1988) proposed an alternative approach. His insight is based on the observation that under perfect competition and constant returns to scale, markups will be equal to one.[6] De Loecker and Warzynski (2012) build on this early work to derive estimates of *firm*-level markups from the cost minimization problem of the firm. In particular, for any production function $\mathcal{F}_{it}(\cdot)$, De Loecker and Warzynski (2012) derive the following expression for the firm markup from the cost-minimization first-order condition:

$$\mu_{it} \equiv \frac{P_{it}}{MC_{it}} = \underbrace{\frac{\partial \mathcal{F}_{it}(\cdot)}{\partial \mathcal{V}_{it}} \frac{\mathcal{V}_{it}}{\mathcal{F}_{it}(\cdot)}}_{OutputElasticity} / \underbrace{\frac{P_{it}^{\mathcal{V}_{it}} \mathcal{V}_{it}}{P_{it} Q_{it}}}_{ExpenditureShare} = \frac{\beta_{it}^{\mathcal{V}}}{\alpha_{it}^{\mathcal{V}}}\ , \tag{1}$$

where μ_{it} is the markup, P_{it} is the output price, MC_{it} is marginal cost, $\mathcal{V}_{it}$ refers to any flexible input, and $P_{it}Q_{it}$ is nominal sales. In short, the firm markup can be estimated as the ratio of the output elasticity of a variable input ($\beta_{it}^{\mathcal{V}}$) to the firm expenditure share on that input ($\alpha_{it}^{\mathcal{V}}$). Expenditure shares can be directly obtained from any dataset containing firm-level information on sales and input expenditure. However, the output elasticity is not directly observable and requires estimation.

Firm-level estimates of the output elasticity cannot be easily obtained but, under the assumption that all firms within a sector share the same technology, it is possible to estimate the following industry-specific Cobb-Douglas production function:[7]

$$q_{it} = \beta_{\nu} \nu_{it} + \beta_k k_{it} + \omega_{it} + \epsilon_{it} \tag{2}$$

where lower cases denote logs, q_{it} represents the log of real sales, ν_{it} is the log of any flexible input (in real terms), k_{it} refers to the log of the real capital stock, ω_{it} stands for firm productivity and ϵ_{it} is the error term including unanticipated productivity shocks and measurement error. The traditional estimation challenge to obtain consistent estimates of the output elasticities is simultaneity bias, due to the likely possibility that the firm-productivity (unobserved to the econometrician but known to the firm) is correlated with the input choice. As De Loecker and Warzynski (2012),

[6] Hall (1986) derives the following expression: $\Delta q = \mu\alpha\Delta n + \varpi + u$; where Δq is the rate of change in output, Δn is the rate of change in labor, μ is the markup, α is the labor share in revenue, ϖ is the average rate of technological change, and u is the error term. Rearranging, the rate of change in output over the rate of change in labor is the labor elasticity so, the markup equals the ratio of the labor elasticity of output to the labor revenue share. The main difficulty is to obtain an unbiased estimate of the input elasticity. Hall (1986) proposes various instrumental variables and Klette (1999) follows a similar approach using GMM estimation.

[7] We follow De Loecker et al. (2020) and consider a Cobb-Douglas production function; in Section 7 we consider alternative assumptions like a translog production function and different richer input structures.

we follow the control function approach literature pioneered by Olley and Pakes (1996) and Levinsohn and Petrin (2003) and updated by Ackerberg et al. (2015). The methodology assumes that productivity follows a first-order Markov process and is a function of the firm's flexible inputs and capital: $\omega_{it} = h(\nu_{it}, k_{it})$.[8] Then the method proceeds in two steps. In the first step, one obtains estimates of the expected output that removes measurement error and unanticipated shocks:

$$q_{it} = \phi_t(\nu_{it}, k_{it}) + \epsilon_{it}, \tag{3}$$

In particular, estimates of expected output are obtained from the following second-order approximation:

$$\phi_{it} = \beta_\nu \nu_{it} + \beta_k k_{it} + \beta_{\nu\nu}\nu_{it}^2 + \beta_{kk}k_{it}^2 + \beta_{\nu k}\nu k_{it} + h(\nu_{it}, k_{it}) \tag{4}$$

For the second stage, the method relies on the law of motion for productivity, which is assumed to be: $\omega_{it} = g_t(\omega_{i,t-1}) + \xi_{it}$, where ξ_{it} are the innovation shocks to productivity and the estimates are obtained by projecting productivity on its lagged value.[9] Based on these steps, the following moment conditions can be formed to obtain the output elasticity estimates:

$$E\left(\xi_{it}(\beta)\begin{pmatrix} \nu_{i,t-1} \\ k_{i,t} \end{pmatrix}\right) = 0 \tag{5}$$

Notice the moment condition for the flexible input uses $\nu_{i,t-1}$ as an instrument and addresses the Ackerberg et al. (2015) critique.[10] This means the firm chooses the flexible input after the capital stock was determined at time $t-1$.

The production function is estimated separately by industry (2-digit NACE Rev.2 industry classification), obtaining a different output elasticity by sector so that the final firm-level markup

[8] Olley and Pakes (1996) use the investment decision to proxy for unobserved productivity while Levinsohn and Petrin (2003) rely on intermediate inputs to proxy for unobserved productivity – the proxy functions. Provided the monotonicity condition is met and intermediate inputs are strictly increasing in ω_{it}, the proxy function can be inverted, allowing to express the unobserved productivity as a function of observable characteristics. De Loecker and Warzynski (2012) argue that the monotonicity of intermediate inputs in productivity holds under a large class of models of imperfect competition.

[9] In practice we project productivity on a third order polynomial of lagged productivity.

[10] Ackerberg et al. (2015) argue that in the traditional Levinsohn and Petrin (2003) approach to estimate a production function using labor, materials and capital inputs, if labor was a function of both productivity and capital, it would not be possible to identify the coefficient on labor in the first stage.

is obtained as:

$$\mu_{it} = \frac{\beta_s^{\nu}}{\alpha_{it}^{\nu}} \tag{6}$$

where β_s^{ν} is the output elasticity of the flexible input ν in industry s and α_{it}^{ν} is the expenditure share of flexible input ν by firm i in period t.[11] According to equation (6), markups are the deviation between the elasticity of output with respect to a variable input and that input's share of total revenue.

3 Data

The main data source of the paper is Orbis, provided by Bureau van Dijk. Orbis contains information on around 300 million companies across the globe. Its main strength lies in the availability of harmonized cross-country financial information for both private and public firms since the mid-90s. Bureau van Dijk gathers data from over 160 providers (usually local companies that collect information from the business registers). Our data were obtained through the "Orbis Historical" product that provides the longest available coverage.[12]

The raw data requires intensive cleaning prior to estimation. The cleaning procedure closely follows Kalemli-Özcan et al. (2015), Gopinath et al. (2017) and Gal (2013). First, the cleaning involves dealing with basic reporting mistakes (i.e., negative sales, total assets, employment, cost of employees, tangible fixed assets or liabilities; missing or zero values for the cost of materials, operating revenue, total assets and missing NACE sectoral code). Second, we implement further quality checks that verify the age of the firm, the ratio of short-term to long-term liabilities, the ratio of employees to capital, tangible fixed assets to total assets, capital to shareholder funds, and total assets to shareholder funds. Finally, we apply filters on the annual growth rates of sales, operating revenues and number of employees. After this cleaning procedure, our data accounts on average for at least 40% of the total output reported in official sources. The U.S. is included in the sample despite a lower coverage in some years and that it includes almost only listed firms

[11] The expenditure share is the ratio of the cost of flexible input ν to sales where sales are corrected for the presence of measurement error as suggested by De Loecker and Warzynski (2012). The estimated distribution of the baseline markup is trimmed at the upper 0.01 percentile.

[12] See Kalemli-Özcan et al. (2015) on how to recover the longest historical series from various disk vintages instead.

due to its relevance in the global economy. Appendix A provides further details on the cleaning procedure.

After the cleaning procedure, the variables used in the production function estimation (need to obtain the elasticity β required for the markup calculation) must be properly deflated. Since the dataset includes information on sectors from multiple countries, one of the main challenges is to find sectoral (2-digit) industry producer price indexes for all countries in our sample. Thus, to deflate variables like revenue, wage bill, material costs, and cost of goods sold, we compiled information on value added and gross output deflators from various sources, including the OECD, Eurostat and government websites, and used the ones that had better coverage across industries and time. When available we used the 2-digit NACE deflator; this was the case for most sectors in European countries and for manufacturing sectors in most other countries. In the absence of 2-digit deflators we used 1-digit NACE industry deflators and in the absence of disaggregated industry deflators we used the overall country GDP deflator. Further, we follow Inklaar and Timmer (2014) and make PPP-adjustments when deflating the different variables. This adjustment is needed to ensure comparability of values across years and countries within industries. To fix ideas, if we had only one country, the production function would be typically estimated by industry after deflating nominal values with industry price deflators. However, our case is more complex because we have multiple countries—we estimate a production function by industry, pooling (firms across) countries, and this requires not only obtaining the real counterparts of the nominal variables but also taking into account the differences in price levels between countries within an industry to ensure that all variables/values within an industry are comparable. Capital is deflated using the WDI PPI-adjusted exchange rates. Ultimately, all variables are expressed in U.S. dollars of 2005. More details on the deflation method can be found in Appendix A. Finally, to strengthen the representativeness and comparability of the sample across countries, we focus on the sample of firms with average employment greater or equal to 20 employees (Calligaris et al. (2018)).

After the cleaning and deflation steps, we have a baseline sample with data on 19 countries mainly for the period 2000-2015 and an alternative sample on 27 countries for 2004-2013. Specifically, the baseline sample includes Belgium, Bulgaria, Czech Republic, Denmark, Estonia, Finland, France, Germany, Great Britain, Greece, Italy, Japan, Korea, Latvia, Portugal, Romania, Russia, Spain and the United States. The alternative sample includes, in addition, Austria, China, Hungary, Ireland, Netherlands, Poland, Slovakia and Slovenia. Appendix Table A.1 presents the list of countries included in our data set. Overall, the countries included in our sample cover over 70 percent of world GDP.[13]

Table 1 shows the summary statistics of the main variables used in the estimation of the production function. Our baseline sample consists of over 5 million observations with an average annual income of $54 million (U.S. dollars of 2005). In addition, the average firm has 192 employees, incurs in sales' costs (directly attributable to production, COGS) of $38.5 million, and possesses capital (proxied by tangible fixed assets) by almost $19 million. Appendix Table A.4 provides summary statistics by country.

Table 1: Summary Statistics

	Turnover	**Capital**	**Costs of goods sold**	**Employment**
Mean	54,450,420	18,725,598	38,484,807	192
P50	5,850,156	665,298	3,905,000	43
P25	1,914,517	111,943	1,256,500	27
P75	17,310,996	2,920,588	12,422,341	87
N	5,776,948	5,752,092	5,776,948	5,205,353

Notes: All monetary variables are expressed in U.S. dollars of 2005. Turnover refers to operating revenue; Capital corresponds to tangible fixed assets; Employment is the number of employees and the variable Costs of goods sold is the direct cost attributable to the production of the goods sold in a company, which includes the cost of the materials used in creating the good along with the direct labor costs used to produce the good. For countries reporting separately material and labor costs, we add these two variables to construct a synthetic costs of goods sold.

4 Baseline Results

4.1 Global Markups

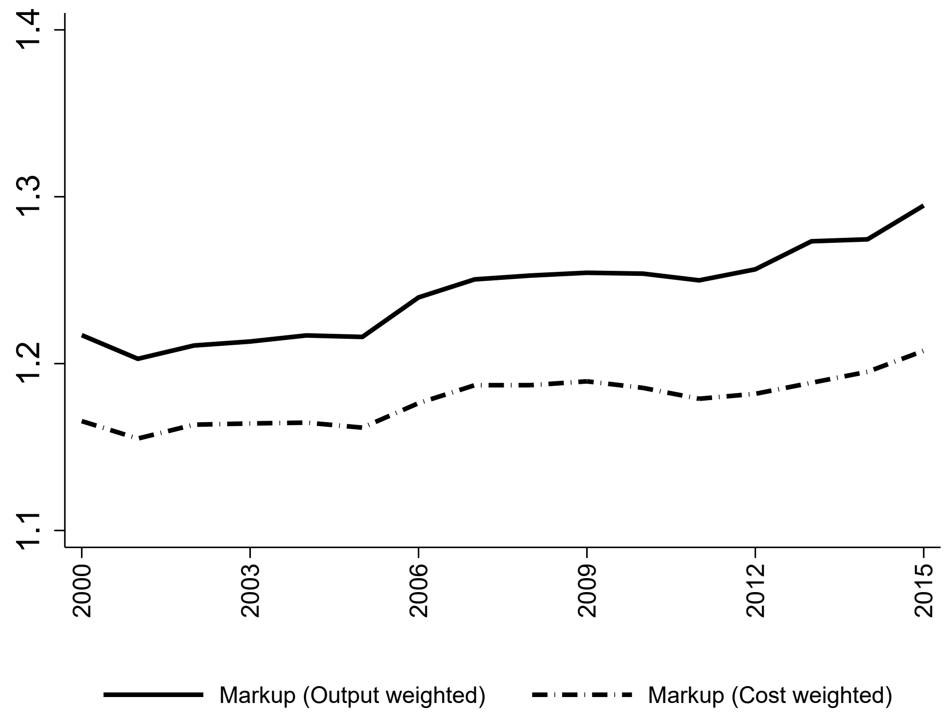
We begin by computing the evolution of the average markup pooling all countries in our sample. For this, we estimate the markups at the firm level, following equation (6), and aggregate up weighting each firm by the share of its revenue or of their costs of goods sold in the sample.

We present the resulting aggregate markups in Figure 1, where we observe that, during 2000–

[13] Appendix Tables A.2 and A.3 provide information on the coverage by country. Data limitations in the time series coverage for some countries, results in Bulgaria, Czech Republic, Germany, Korea, Portugal, and Russia starting 1-2 years after the rest of the baseline sample.

2015, markups have increased from around 1.22 to 1.29 when weighted by revenue and from almost 1.17 to 1.21 when weighted by costs. From comparing both lines, it is clear that the cost-weighting approach delivers lower average markups levels (like in Edmond et al. (2018)), but the trend is very similar using either sales or cost weights. This corresponds to stylized fact (**F1**).

Figure 1: Average Global Markup



Notes: The solid line reports markups weighted by firm's revenue and the dashed-line report markups weighted by firm's expenditure on inputs (cost of goods sold - COGS). The figure uses the countries in the baseline sample.

Reassuringly, the different weighting schemes deliver a similar message: a limited increase in markups.[14] In what follows we present the results using revenue weights while the cost-weighted results are presented in the Appendix. The choice of weighting scheme does not alter the main findings of the paper and there are advantages to using the revenue-weight approach as the baseline. First and foremost, it ensures full comparability with already established results in the literature using output-based weights (see De Loecker et al. (2020), De Loecker and Eeckhout (2020), Traina

[14] In Appendix Figure B.1 we consider additional possible weighting schemes like value added or wage bills—from the figure it is clear that the moderate increase in average markups is robust to all alternative weighting schemes. All weighting schemes used for aggregation are winsorized at the 1 and 99 percentiles. Further, in Section 7 we document that the baseline results on markup dynamics are robust to alternative estimation techniques, concerns about changing technology and about the role of overhead costs in the production function.

(2018), Karabarbounis and Neiman (2018) and Autor et al. (2020)). In addition, it provides internal consistency within the paper as output-based measures are used to study the role of reallocation versus within changes in later sections of the paper. Finally, absent an aggregate-level equivalent to equation (6), our aggregate object of study is the average of the firm-level markups, and the choice of the weighting scheme should be in line with the economic phenomenon at hand—thus, since the paper focuses on competition in *product* markets, using output weights is the most sensible choice (instead, if the paper were to focus on welfare analysis, cost weights would be the most suitable approach; see Edmond et al. (2018)).

As discussed in Section 2, this increase in markups would suggest a modest decline in global competition. This interpretation is further strengthened by the observed simultaneous increase in profitability. Indeed, in Appendix Figure B.2 we show that firms' operating margins have also increased during this period (under both, revenue and cost weights) and, moreover, in Appendix Table B.5 we show that there is a strong association between firm profitability and markups, even after controlling for firm fixed effects, country-four-digit industry fixed effects, size, and overhead costs—all of which provides further evidence that the increase in markups, although quantitatively modest, corresponds to an increase in market power.

Further, the markup increase reported in Figure 1, while significant, is much more moderate than the one found by De Loecker et al. (2020), De Loecker and Eeckhout (2020), and Díez et al. (2018), even when considering the latter part of their samples that overlaps with our sample's time span. Since the methodology we employ is the same as in these other papers (precisely for comparison purposes), there are two factors that can explain this discrepancy: differences in the set of countries considered and, most importantly, the fact that our analysis considers the whole distribution of firms (listed and private).[15] Indeed, as we show below, the average markup increase for private firms is significantly lower than for listed firms—resulting on aggregate markups (that combine listed and private firms) increasing quite less than what was previously found in the literature. In fact, if we restrict our sample to just listed firms, our results are very much in line with the findings by De Loecker et al. (2020) or De Loecker and Eeckhout (2020). In light of this,

[15] The final version of De Loecker et al. (2020) has a complementary section using data on private firms for 3 sectors: manufacturing, retail, and wholesale. However, their analysis is not entirely comparable since the data are at a 5-year frequency and the latter 2 sectors do not contain information on non-labor inputs. The average estimated markups range between 1.8 and 6 during the overlapping period. Further, our findings are in line with those by Calligaris et al. (2018) which are also based on Orbis.

in the remainder of this section, we study the importance of the firm distribution from different angles, focusing on the difference between listed and private firms for a better comparison with the existing literature, exploring the differences depending on sectors or regions, and documenting the composition and characteristics of high-markup firms, including the role of firm size.

4.2 Listed vs Private Firms

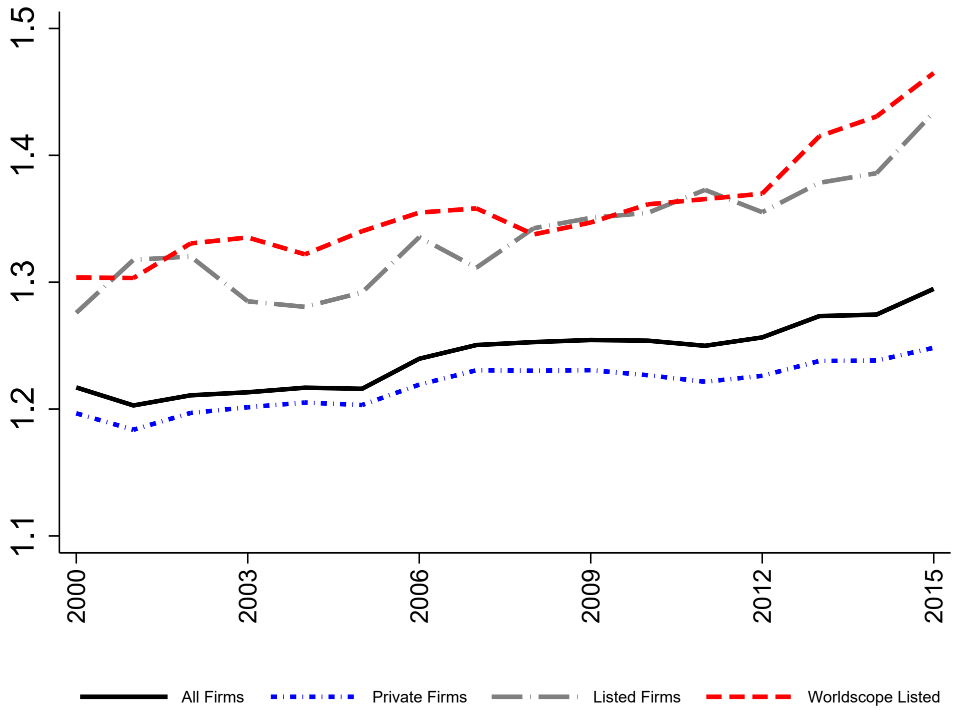
To benchmark our results with the previous literature that focused mainly on the evidence of listed firms (see, e.g., De Loecker et al. (2020), De Loecker and Eeckhout (2020), Díez et al. (2018)), we breakdown the evolution of markups for publicly listed and privately held firms. This decomposition is critical to understand one of the main contributions of our paper since it allows us to dissect the data and isolate what is the behavior of each type of firm—namely, whether private firms, that constitute the vast majority of firms but are much less studied in the literature, present different dynamics and, if so, whether this is quantitatively relevant.

Figure 2 presents the markups by firm type. The black solid line reports our baseline (overall) result and the dashed grey and blue lines the average markup of listed and private firms, respectively. Further, the figure also plots a red dotted line, that reports the average markup of listed firms using information from another data provider, Worldscope, widely used in the literature.[16] There are two takeaway messages from the figure. First, it is clear that the average markups of listed firms are higher than those of private firms. Second, the increase in markups was more pronounced among listed firms (12%) than among private firms (4%). This corresponds to stylized fact (**F2**). In addition, as in the case of the baseline results, cost-weighted markups deliver similar trends, albeit with different levels (see the cost-weighted results in Appendix Figure B.3).

In summary, these findings illustrate how different types of firms have different markup dynamics. Crucially, these findings also provide a novel view and explain why, contrary to common wisdom, on average, global markups have increased only slightly since 2000.

[16] The use of Worldscope data allows for a direct comparison to results in De Loecker and Eeckhout (2020) and alleviates concerns about the coverage of listed firms in Orbis. The information in Orbis regarding the listed status of the firm is time-invariant and identifies if the firm is listed, unlisted or delisted. It is reassuring that results are very similar regardless of the data provider. See Díez et al. (2018) for a description of the Worldscope dataset. Markups were computed as $\mu_{it} = \beta_s * \alpha_{it}$, where β is the COGS elasticity from a production function estimated by sector using Worldscope information from 2000-2015 and α_{it} is obtained directly off the data and was winsorized at the 1 and 99 percentiles.

Figure 2: Average Global Markup – Private vs Listed Firms



Notes: The black-solid line reports the average markups of all firms; the blue-dashed line reports average markups of private firms; the grey-dashed line reports average markups of listed firms in Orbis; and the red-dotted line reports markups of listed firms in Worldscope. Markups averaged using firm revenue weights. The figure uses the countries in the baseline sample.

4.3 Sector and Country Disparities

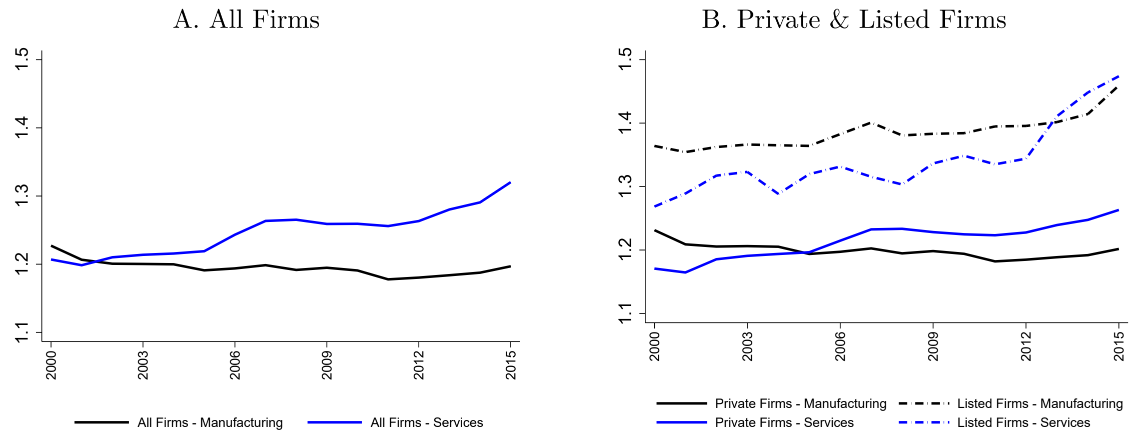
After having established the sharp differences in markup dynamics stemming from the type of firms considered, we further exploit the granularity of our dataset. In particular, in this subsection we zoom into the cross-sector and cross-country dimensions and identify patterns that hold across sectors (i.e., markup evolution of manufacturing and service sectors) and regions (i.e., markup evolution in advanced economies and emerging markets). Further, we also show that the differences between listed and private firms' markups still hold when comparing these different groupings.

We first focus on the difference in markup dynamics across broad sectors. Figure 3 plots the disparate evolution of markups for manufacturing and for services. Panel A shows that while manufacturing markups have remained flat (and even decreased slightly, consistent with De Loecker et al. (2020) for the overlapping period), markups in services have shown an upward trend (increasing from 1.21 to 1.32)—this corresponds to the first comment qualifying stylized fact (**F1**). Further, the second panel of the figure confirms the same patterns already found for private vs listed firms. That is, the markups of listed firms are clearly above those of private firms for both manufacturing and services; and listed firms show larger increases than private ones, again for both manufacturing (7% vs -2%) and services (16% vs 8%). While at first this may seem surprising and contrary to popular belief, one must bear in mind that, for instance, the majority of the big tech firms are not manufacturers. Rather, they are counted among service providers in industries like computer programming, publishing activities, or retail trade. Thus, the rise of these corporate giants occurs mostly within the service sectors—of course, this does not imply that there are no manufacturing firms within this group; rather, that the majority of them actually are service firms (i.e., more generally, there are just 2 manufacturers among the top-20 firms in the S&P500 index).

Greater disaggregation reveals even more substantial heterogeneity, as shown in Appendix Figure B.4. For instance, some sectors present large increases (like accommodation and food services, financial services, real estate, or utilities), while others have small increases (like wholesale and retail trade or transport and storage), and yet others have outright flat markups (construction, or administrative services). Moreover, there is also pervasive heterogeneity within narrower sectors—for example, markups increased by 7.5% in the one digit industry "wholesale and retail trade" however, the increase of markups in retail is three times that of wholesale (12% vs 4%, respectively); or there is a 3% decrease in the markups of motor vehicles but a 4% increase in other transport equipment (e.g., ships, air and space transport). While the study of the underlying forces behind this cross-sectoral differences is beyond the scope of the paper, it is worth mentioning the role played by the surge of the digital economy. Indeed, as shown in Appendix Figure C.1, those sectors that are more intensive on their *use* (not production) of ICT technologies show a larger increase in their markups (in line with the findings in Calligaris et al. (2018)).

We next turn to explore the differences across countries. We begin by distinguishing the evolution of markups between advanced economies and emerging markets, as shown in Figure 4 (for this part of the analysis we use the alternative sample described in Section 3 that covers a shorter time span but includes a larger number of emerging markets). Panel A plots the markups for the advanced economies and for the emerging markets—it is clear that markups have increased in advanced economies (from 1.19 to 1.25) while they have remained essentially flat (at 1.18) among emerging markets. Panel B zooms into these differences distinguishing between private and listed

Figure 3: Sectoral Differences



Notes: In Panel A, the black-solid line reports the average markup in the manufacturing sector and the blue solid line reports the average markup in the service sectors. Panel B repeats the analysis for the sample of Orbis private firms and Worldscope listed firms. Service sectors in Orbis include Nace Rev 2 one-digit codes: G to S. Service sectors in Worldscope include from SIC 40 until SIC 99 excluding SIC2-49. Markups averaged using firm revenue weights. The figure uses the countries in the baseline sample.

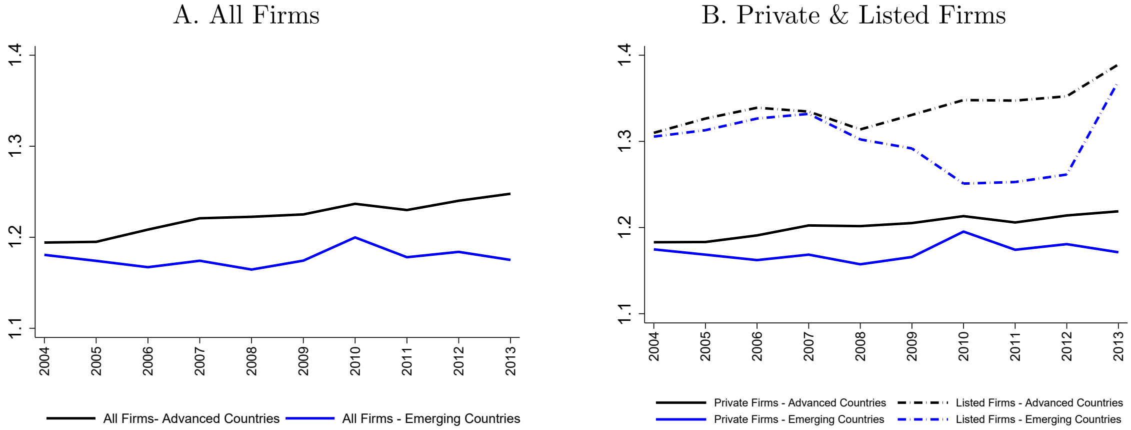
firms and, once again, listed firms' markups lie above private firms' markups. Further, in terms of markup dynamics, the figure shows a moderate increase for private and somewhat larger for listed firms in advanced economies. In the case of listed firms in emerging markets, the figure first shows a downward trend of markups, followed by a surge from 2012 onwards, in line with the findings of De Loecker and Eeckhout (2020). On the contrary, the markups of emerging markets' private firms remained flat during this period.

Taken together, these results show that the global increase in markups is driven by the advanced economies, whose markups steadily increased by almost 5% during 2004–2013. This is in sharp contrast with the markups for the emerging markets which, on aggregate, remained practically unchanged during the period considered.[17] This corresponds to the second qualifying comment on stylized fact (**F1**). In the Appendix we further unpack the results by country: Appendix Figures B.5 and B.6 show there exists substantial heterogeneity across regions—for instance, the U.S. and Asian countries appear as polar opposites in terms of levels and increases, while European countries (especially Western ones) lie somewhere in between.[18]

[17]It should be noted that the relative importance of listed firms in emerging markets is significantly smaller than in advanced economies. In fact, the median number of listed firms among the former group is 330 while the median among the latter group is just 55.

[18]Further, for the handful of countries for which there is a sufficiently large number of listed firms, we confirmed that the differences between listed and private firms discussed above also hold at the country level.

Figure 4: Geographical Differences



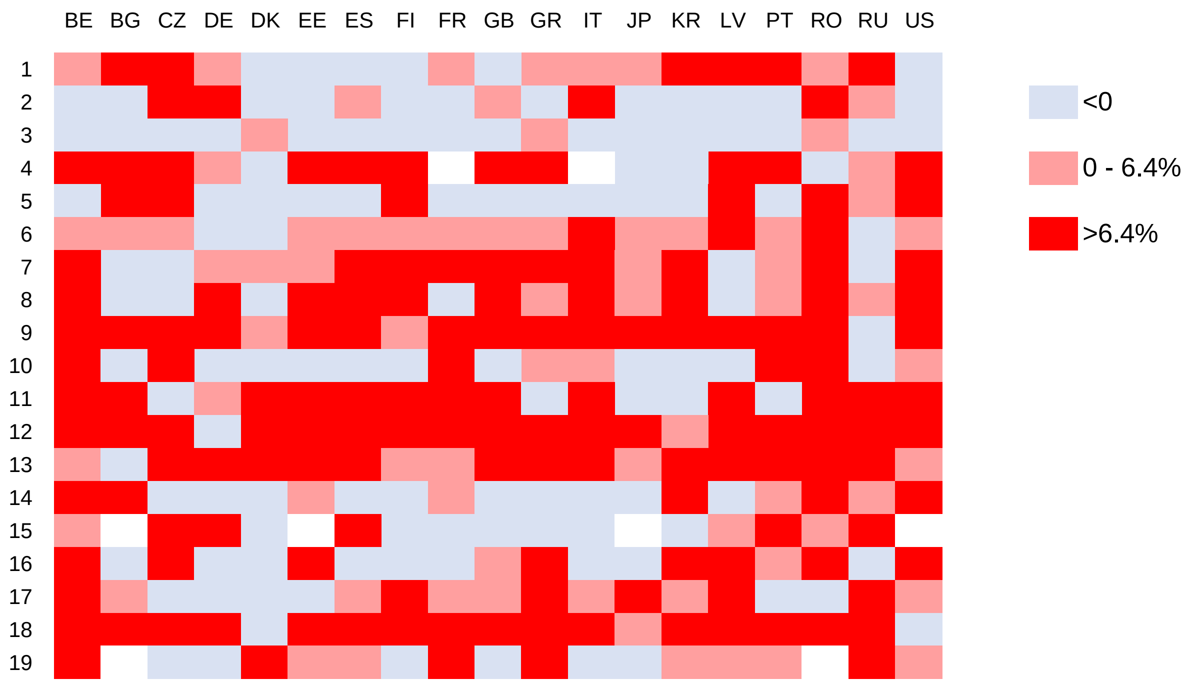
Notes: The definition of advanced economies used follows the IMF's World Economic Outlook classification in 2000 (the first year in the data set). In Panel A, the black-solid line reports the average markup in advanced countries and the blue solid line reports the average markup in emerging countries. Panel B repeats the analysis for the sample of Orbis private firms and Worldscope listed firms. Markups averaged using firm revenue weights. The figure uses the countries in the alternative sample.

Finally, we close the analysis of this subsection by looking at the joint country-sector changes in markups. Specifically, the heatmap presented in Figure 5 provides a snapshot of the overall changes observed throughout our sample period for each country-sector pair. From the figure it is apparent that there are significant differences across both sectors and countries. However, it is also apparent from the figure that the sectoral differences are more significant than the cross-country differences. For example, while the increases in Belgium were more widespread than in Bulgaria, the differences across sectors are much more pronounced. For instance, sectors 12 (real estate activities) and 13 (professional activities) increase across almost all countries whereas the increases in sectors 2 (mining) and 3 (manufacturing) are much less common. Further, it is also worth noting that some sectors are more likely to show markup increases among certain types of countries than others—increases in sectors 7 (wholesale and retail trade) and 8 (transport and storage) are more common across advanced economies whereas increases in sectors 4-5 (utilities) are more common among emerging markets.

4.4 High-Markup Firms: Full Firm Distribution

In this subsection, we go a step further in exploiting the richness of our data and explore the characteristics of high-markup firms in the entire markup distribution, i.e., regardless of their legal status—something that turns out to be of first order importance in understanding markup

Figure 5: Change in Average Markup by Country – Sector



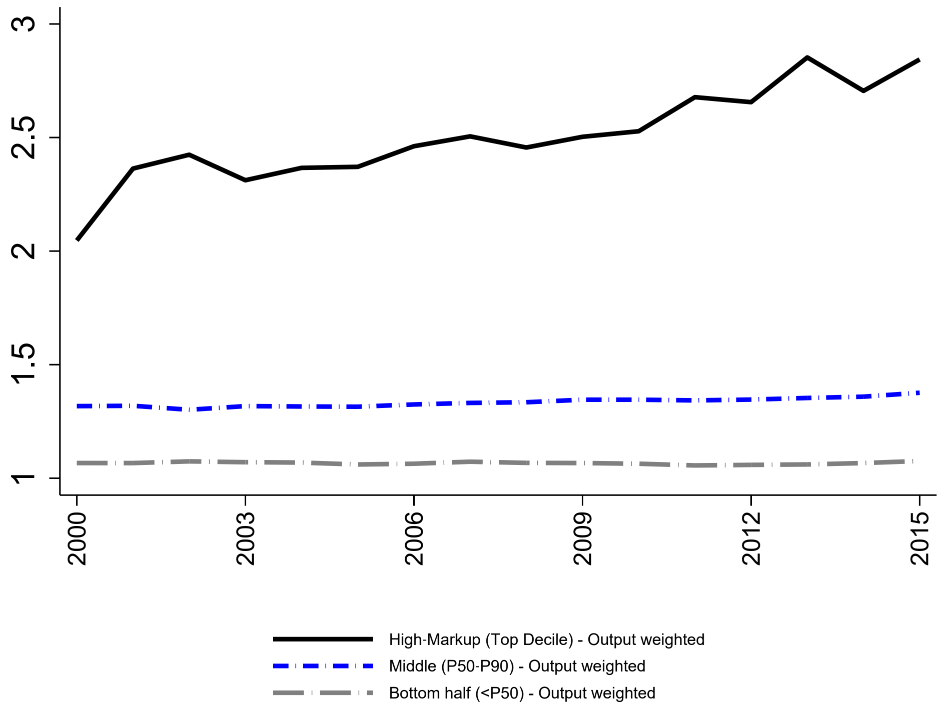
Notes: Each cell represents the change in markup between the first and last years for the corresponding country-sector pair. Markups averaged using firm revenue weights. The figure uses the countries in the baseline sample. Country codes: BE (Belgium), BG (Bulgaria), CZ (Czech Republic), DE (Germany), DK (Denmark), EE (Estonia), ES (Spain), FI (Finland), FR (France), GB (United Kingdom), GR (Greece), IT (Italy), JP (Japan), KR (Korea), LV (Latvia), PT (Portugal), RO (Romania), RU (Russia) and US (United States). Industry codes: 1 (Agriculture, forestry and fishing), 2 (Mining and quarrying), 3 (Manufacturing), 4 (Electricity, gas, steam and air conditioning supply), 5 (Water supply; sewerage; waste management and remediation activities), 6 (Construction), 7 (Wholesale and retail trade; repair of motor vehicles and motorcycles), 8 (Transporting and storage), 9 (Accommodation and food service activities), 10 (Information and communication), 11 (Financial and insurance activities), 12 (Real estate activities), 13 (Professional, scientific and technical activities), 14 (Administrative and support service activities), 15 (Public administration and defence; compulsory social security), 16 (Education), 17 (Human health and social work activities), 18 (Arts, entertainment and recreation) and 19 (Other services activities).

dynamics. We start by documenting the evolution of markups for different moments of the markup distribution and then we explore the general characteristics of high-markup firms, including the relationship with size.

The documented overall 6% increase in global markups conceals substantial heterogeneity stemming from the co-existence of three groups of firms that stand out when analyzing the entire distribution of markups: the high-markup firms that correspond to the upper decile of the markup distribution; the firms in the middle group located between the median and the 90th percentile; and the firms below the median.[19]

[19]The deciles to assign firms to the different groups were computed by calculating the average markup of each

Figure 6: High-markup, Middle, and Laggard Firms



Notes: High-markup firms (black-solid line) are those firms in the upper decile of the markup distribution; middle firms (blue-dashed line) as those between the median and the 90th percentile; bottom half firms (gray dashed line) are those below the median of the distribution. Markups averaged using firm revenue weights. The figure uses the countries in the baseline sample.

Figure 6 plots the evolution of markups for the firms in each group. The differences between groups are stark: while the high-markup firms increased their markups by 40%, the firms in the bottom half kept their markups unchanged and those in the middle of the distribution increased markups only slightly (similar results are found when using input costs weights, as shown in Appendix Figure B.7). This corresponds to stylized fact (**F3**). The percentiles shown in the figure are chosen to illustrate that most of the action takes place on the upper parts of the distribution (i.e., the markup increases are larger as one moves further up the upper percentiles of the markup distribution).

The question naturally arises: who are these high-markup firms? Based on the evidence presented in the previous section, listed firms come first to mind—however, this is quite an incomplete answer. While the 12% markup increase of listed firms is substantial (twice the increase in the

firm during the whole sample; thus, the deciles are time-invariant. It follows that high-markup firms do not only show higher rates of growth in markups but also by construction display higher average markup levels. The results are robust to recomputing the deciles every year.

overall sample), it is clear that it cannot account for the notable 40% increase of the top decile of the markup distribution. As a matter of fact, the group of high-markup firms is composed by listed firms but also by many other private firms, including both large and small ones. Indeed, the majority of firms in the top decile are private—not surprisingly since private firms account for over 98% of all firms in the sample—although a listed firm is almost twice as likely to be in the top decile than a private firm: almost 20% of listed firms belong to this decile vs. 10% of private ones. In addition, while the majority of firms in the top decile are small (with revenues below the median), the top decile also includes very large firms. In fact, the 10% largest firms in the top decile account for over 90% of the decile's revenue or, in other words, 1% of firms (10% of the decile) explain 8% of overall revenue in the sample. Even further, this group of large firms includes listed and (a majority of) private firms. In short, the top decile of markups is composed by listed and private firms, and includes both large and small firms.

This suggests that to study markups relying just on listed firms can be misleading as the mass of firms ignored is not just concentrated on one tail of the distribution but, rather, it is spread throughout the entire distribution of markups—including the crucial right tail driving markup dynamics. This compositional finding corresponds to the second part of fact (**F3**).

Further, high-markup firms are also highly performing firms. Indeed, conditional on size, they are 20% more productive, report 3% higher profits and are more likely to spend on intangible assets (see Appendix Table B.6). Moreover, high-markup firms are found in all broad economic sectors (see Appendix Table B.7). This confirms the evidence on substantial heterogeneity in markups within sectors. The dispersion in markups is not limited to broadly defined sectors—in a similar fashion as Syverson (2011), who finds large productivity differences within narrowly defined sectors, we also find significant differences in firm markups within four-digit industries that, importantly, have been increasing over time (see Appendix Figure B.8). While not conclusive, this evidence could suggest that as the digital wave progressed encompassing more sectors, it allowed for winner-takes-most dynamics and the surge of superstar firms (in the spirit of Autor et al. (2020)) that could partly explain some key markup features observed in the data.

This compositional finding may be a priori counter-intuitive (i.e., high-markups firms not being limited to listed firms and including an important share of large and small private firms), but it can be rationalized in (at least) two ways. First, one can think of product differentiation where firms operate in *niche* markets as described by Holmes and Stevens (2014).[20] This might include firms that choose to keep their market share small to exploit preferences for exclusivity (e.g., luxurious goods) or firms producing specialized goods (e.g., made-to-order goods). These firms optimally remain small in size but still manage to set high markups. A second possibility refers to cases where there is market fragmentation and barriers to entry and consequently firms, being able to avoid competition and limited to a fragmented market, remain small while charging high markups (e.g., retail shops in remote locations). Therefore, high-markup small firms (typically private) can co-exist with large high-markup firms. As already suggested, it follows that the exclusion of private firms from the analysis affects the entire distribution of markups and not just one tail. Given the findings in this section, we next turn to analyze in detail the relationship between firm size and markups.

5 Markups and Size

5.1 Cross-Sectional Decomposition

To begin the analysis of markups and firm size, we follow De Loecker and Eeckhout (2017) and use the following decomposition proposed by Olley and Pakes (1996):

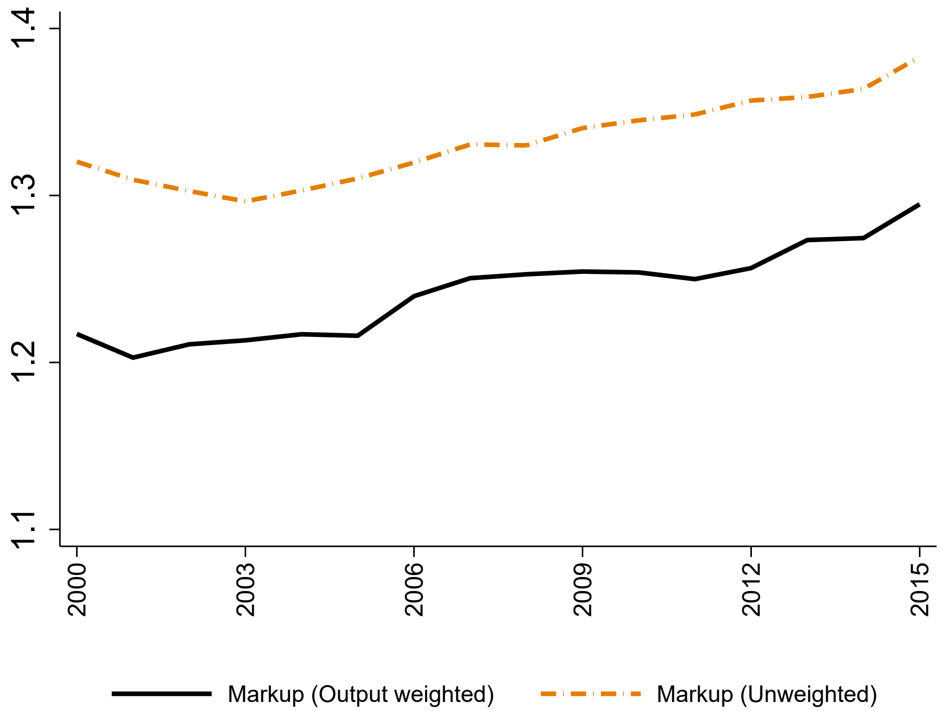
$$\mu_t = \sum_i s_{it}\mu_{it} = \bar{\mu}_t + \sum_i (s_{it} - \bar{s}_t)(\mu_{it} - \bar{\mu}_t) \tag{7}$$

where μ_t is the firm-revenue-weighted average markup; s_{it} is the share of firm i's revenue ($P_{it}Y_{it}$) in total revenue in the economy ($S_t = \sum_{i,t} P_{it}Y_{it}$); $\bar{\mu}_t$ is the unweighted average of markups and the second term shows the covariance between firm size (s_{it}) and firm markup (μ_{it}).

In Figure 7, μ_t is the black solid line, $\bar{\mu}_t$ is the orange line, and the difference between the two is the last term in equation (7) representing the covariance between the firm size and markup. The fact that the weighted average is always below the unweighted average implies that larger firms have lower markups. This covariance term has slightly increased since the global financial crisis. De Loecker and Eeckhout (2017) find a similar result and argue that although the previous

[20] Further, Neiman and Vavra (2019) show the rise of *niche* consumption by households. Recall that our cleaning procedure excludes the micro-firms, so the analysis focuses on small (but not micro), medium, and large firms.

Figure 7: Markup and Firm Size – Unconditional Correlation



Notes: The black-solid line plots the weighted average markup (markups weighted by firms' revenue). The orange-dashed line reports the unweighted average markup. The figure uses the countries in the baseline sample.

result holds across all firms and all sectors, within narrowly defined industries there is instead a positive relationship between markups and size. To show this last point they implement the following decomposition:

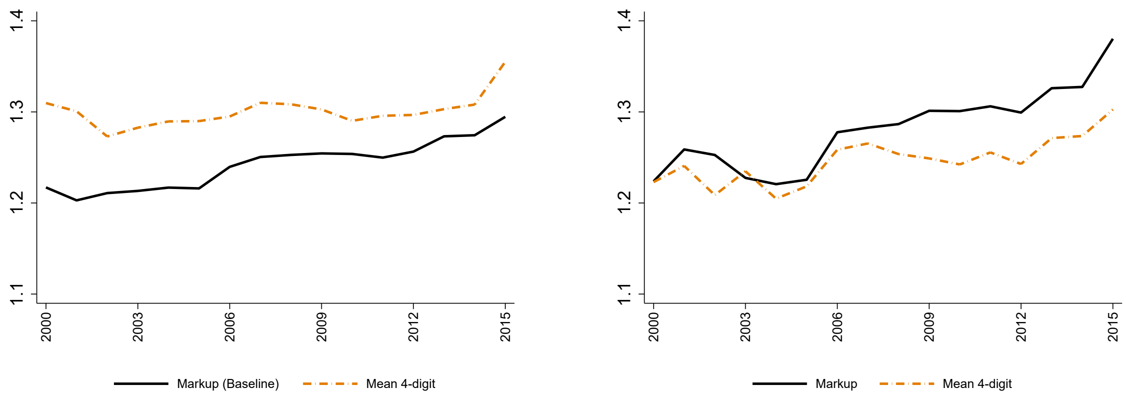
$$\mu_t = \bar{M}_t + \sum_s (s_{st} - \bar{s_{st}})(\mu_{st} - \bar{M}_t) \tag{8}$$

where $\bar{M}_t = \frac{\sum_s \mu_{st}}{S_t}$ is the unweighted sectoral average (we use the four-digit industry sectoral classification) and S_t represents total revenue.

In Figure 8 we present our findings after conducting this same decomposition. The black line in Panel A shows the average weighted markup (μ_t) while the orange line shows $\bar{M}_t$. Panel A shows the negative correlation holds even within narrowly defined industries, although the negative covariance has been decreasing over time, especially in recent years. However, Panel B shows that the within sector correlation is positive for large firms (defined as the top 1% in terms of revenue), in line with the results shown in De Loecker and Eeckhout (2017) using data for listed U.S. firms. It follows that markups and firm size are (unconditionally) negatively correlated except at the top of the size distribution. Next, we further explore this relation to shed some extra light and reconcile our findings.

Figure 8: Markup and Firm Size – Sectoral Decomposition

A. All Firms B. Large Firms



Notes: In Panel A the black-solid line reports the weighted average markup (markups weighted by firms' revenue) and the orange-dashed line reports the unweighted sectoral average (four-digit industry sectoral classification). Panel B repeats the analysis for the sample of large firms (top 1% in terms of sales). The black-solid line reports the unweighted average markup while the dash-orange line reports the unweighted sectoral average. The figure uses the countries in the baseline sample.

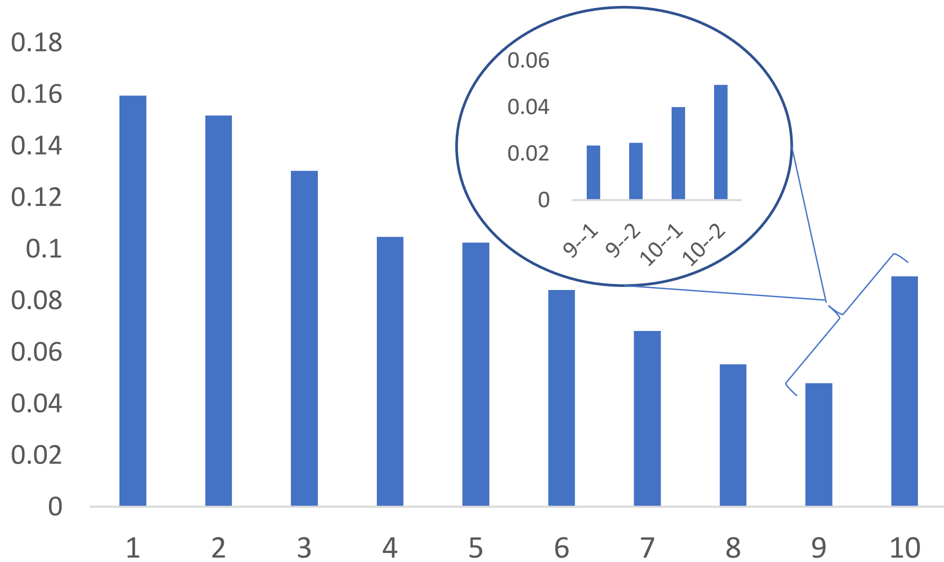
5.2 A U-Shaped Relationship

In this subsection we show that the relationship between firm markup and size is in fact non-monotonic. We begin by plotting the share of average revenue by the firms in each decile of the markup distribution in Figure 9. It is apparent from the figure that, while markup and size are overall negatively related, there is a positive relationship when focusing on the two upper deciles. Zooming into these two upper deciles we observe that the relationship is increasing even within each of these top deciles. Thus, there seems to be an (unconditional) non-monotonicity.

We next look at the relationship between markups and size conditioning on firm observable characteristics. Specifically, Table 2 shows the correlation between firms' markups and size (measured by the market share of firm output in total country-four-digit industry-year output) conditioning on country-four-digit industry-year fixed effects.[21] Columns (1) to (3) show the cross sectional results while columns (4) to (6) show the within-firm results, that is, when firm fixed

[21]Similar results are found if employment is used as a measure of firm size (see Appendix Table B.8)). Furthermore, the findings are robust to having one period lagged values of the regressors.

Figure 9: Share of Revenue per Decile



Notes: Each bar (representing a decile of the markup distribution) plots the share of total average revenue of the decile in total average revenue. Zoomed-in area splits the last two deciles in halves.

effects are included.

Column (1) reinforces the unconditional results commented above: larger firms charge, on average, lower markups. However, in column (2) we find that the relationship is not linear. The positive coefficient on the quadratic term suggests that the relation between markup and size is first negative and eventually becomes positive. The total effect varies by firm size and only becomes positive for firms above the 99th percentile of the market share distribution (similarly, when using employment the turning point is close to 900 employees). The remaining columns in Table 2 show that the results are robust to controlling for differences in productivity and overhead costs across firms (column (3)) and that similar effects are found when including firm fixed effects (columns (4)-(6)). This non-monotonicity corresponds to the last part of stylized fact (**F3**).

6 Dynamic Decomposition with Firm Entry and Exit

In this section, we quantify the relative contributions of surviving firms, firm entry and firm exit to aggregate markup changes. Specifically, we follow Melitz and Polanec (2015) to decompose

Table 2: Markups and Firm Size: Conditional Correlation

Dependent Variable: log Firm Markup

	(1)	(2)	(3)	(4)	(5)	(6)
	Cross-Section			Within Firm		
MS	-0.384***	-1.218***	-1.541***	-0.464***	-1.415***	-1.337***
	(0.005)	(0.011)	(0.021)	(0.006)	(0.015)	(0.023)
MS^2		1.296***	1.619***		1.275***	1.201***
		(0.015)	(0.026)		(0.016)	(0.023)
$\log TFP$			0.676***			0.915***
			(0.006)			(0.006)
$\log Overhead$			-0.025***			-0.027***
			(0.000)			(0.000)
Observations	5,733,006	5,733,006	2,345,336	5,626,481	5,626,481	2,251,882
Firm FE	no	no	no	yes	yes	yes
Country-Ind-Year FE	yes	yes	yes	yes	yes	yes
Cluster	id	id	id	id	id	id

Notes: The dependent variable is the log of firm markup. Firm-level markups are estimated according to equation (6). MS refers to the market share measured as the share of firm sales in total country-sector-4-digit-year sales. $\log TFP$ stands for the log of total factor productivity. $\log Overhead$ stands for the log of other operating expenses. Columns (1) to (3) do not include firm fixed effects. Columns (4) to (6) include firm fixed effects. Standard errors are clustered at the firm level are reported in parentheses.

the overall increase in average firm markups into the contribution by incumbent, entering and exiting firms. In addition, we decompose the effect of each type of firm into a "within component" (i.e., how much of the markup increase is driven by increases in average firm markups) and a "reallocation component" (i.e., how much of the markup increase is driven by larger firms increasing their market shares).[22]

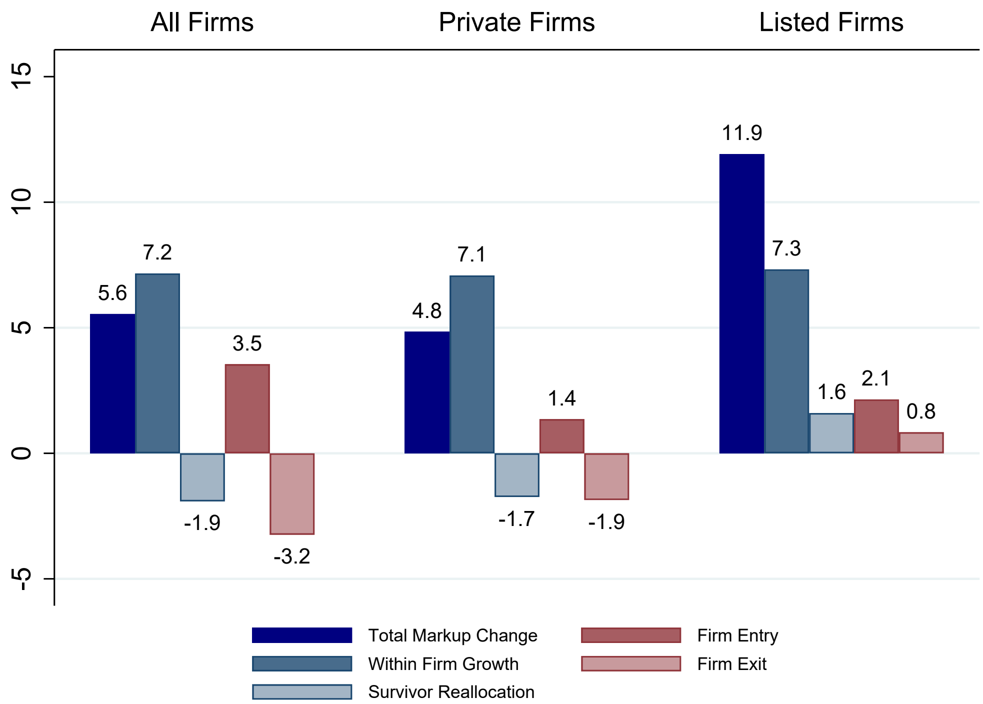
We look at the period 2000-2015 and compute the decomposition for the total sample of firms, and the breakdown between private and listed. We define incumbent firms as those that were present both in 2000 and in 2015. Entering firms are those that were not in the sample in 2000 and appear in the sample in 2015. Exiting firms are those that were present in 2000 but did not report any financial information in 2015.[23]

Figure 10 reports the decomposition results. We first discuss the results for all firms. The

[22] Appendix D shows the details of the Melitz and Polanec (2015) decomposition in levels.

[23] Similar results are found if we were to exploit the age information in Orbis and define entrants as those that were not in the sample in 2000 and by 2015 report at most 15 years of age and exiting firms as those that were present in 2000 but did not report any financial information between 2001 and 2015. We refrain from exploiting the age information so that we can use the same decomposition method for Orbis and Worldscope where company age is only available for a very limited number of firms. Further, notice the precise definition of incumbent, entering and exiting firms leaves out of the current sample firms that entered after 2000 and exit before 2015.

Figure 10: Melitz-Polanec Decomposition of the Change in Markup



Notes: The figure reports the change in markup between 2000 and 2015 and the corresponding decomposition for the sample of All firms and Private firms in Orbis, and Listed firms in Worldscope. Survivor firms are those that were present in 2000 and in 2015. Entering firms are those that were not in the sample in 2000 and appear in the sample in 2015. Exiting firms are those that were present in 2000 but did not report any financial information in 2015. For survivor firms, within firm growth is the difference in the average markup of incumbent firms between 2000 and 2015. The market share reallocation is the difference between the covariance between firm markup and market share of incumbent firms in 2000 and 2015. Markups averaged using firm revenue weights. The figure uses the countries in the baseline sample.

average markup increase in this sample of firms between 2000 and 2015 is 5.6%. We find that 95% of the overall markup increase between 2000 and 2015 is explained by markup increases by incumbent firms. In terms of the extensive margin, entering firms positively contribute to the markup growth during the period, while the contribution of exiting firms is more limited and brings the markup growth rate down. The effect of net entry accounts for the remaining 5% of the overall increase.

The breakdown of the incumbents' effects between within and reallocation effects presents some interesting differences. The within-firm increase (measured by the unweighted mean change in the markup of incumbent firms between 2000 and 2015) explains most of the increase in average markups for incumbent firms. However, there is a negative reallocation effect (measured as the change in the covariance between firm markup and market share in 2000 and 2015) that brings the markup increase down and suggests that over time, within the sample of incumbent firms, the covariance between firm markup and market share has decreased. Entering firms also contribute significantly to the observed markup increase during the period. Interestingly, in this case the relative importance of the within and reallocation effects is reversed. There is a significant increase in their reallocation term (measured by the difference between the covariance of markup and market share of entrants and the corresponding covariance of incumbent firms), accounting for almost the totality of the overall increase and implying that entrants with high markups have higher market shares compared to incumbent firms.[24] In short, the markup increase between 2000 and 2015 can be mainly explained by increases in the average markup of incumbent firms and by sizable reallocation effects towards new firms that gain market share during the period compared to incumbent firms. This corresponds to stylized fact (**F4**).

Next we focus once again on the comparison between private and listed firms to examine whether we observe a differential pattern. The middle and left charts of Figure 10 plot the corresponding decomposition for the sample of private and listed firms. The decomposition for private firms closely follows the overall decomposition. In contrast, the decomposition for listed firms shows some distinguishing features. Indeed, we find that incumbents explain 75% of the overall markup increase and, most importantly, while the within-firm average markup explains most of the increase (as is the case for private firms) the reallocation effect explains 17% of the total incumbent's effect on the average markup increase. Therefore, in the case of listed firms, market share reallocation positively contributes to the overall markup increase. Furthermore, it should be noted that this pattern is even strengthened if we conduct the decomposition only for the U.S., a subsample containing a significant fraction of the largest firms in the world. In this case, the overall markup increase is almost three times the *global* average (15.5%) and, moreover, the contribution of the reallocation component exceeds that of the within-incumbent component (that only accounts for 17% of the overall markup increase). These findings are consistent with Baqaee and Farhi (2019), that using data on U.S. listed companies find evidence consistent with resources being allocated towards high-markup firms and with the findings on superstar firms by Autor et al. (2020).[25] Thus, the data suggest that a significant difference between the U.S. firms

[24]In the case of exiting firms, their contribution is rather small and mainly driven by the fact that the average markup of exiting firms is higher than the average markup of incumbent firms in 2000.

[25]We thank Farhi for his insights on this topic.

and the rest of our sample (mainly European firms) has been a large reallocation of resources away from low-markup, low-productivity firms toward high-markup, high-productivity firms.

7 Alternative Specification and Methodology

In this section we show that the baseline markup results are robust to a wide range of alternative specifications. These range from functional form choices to technological assumptions.

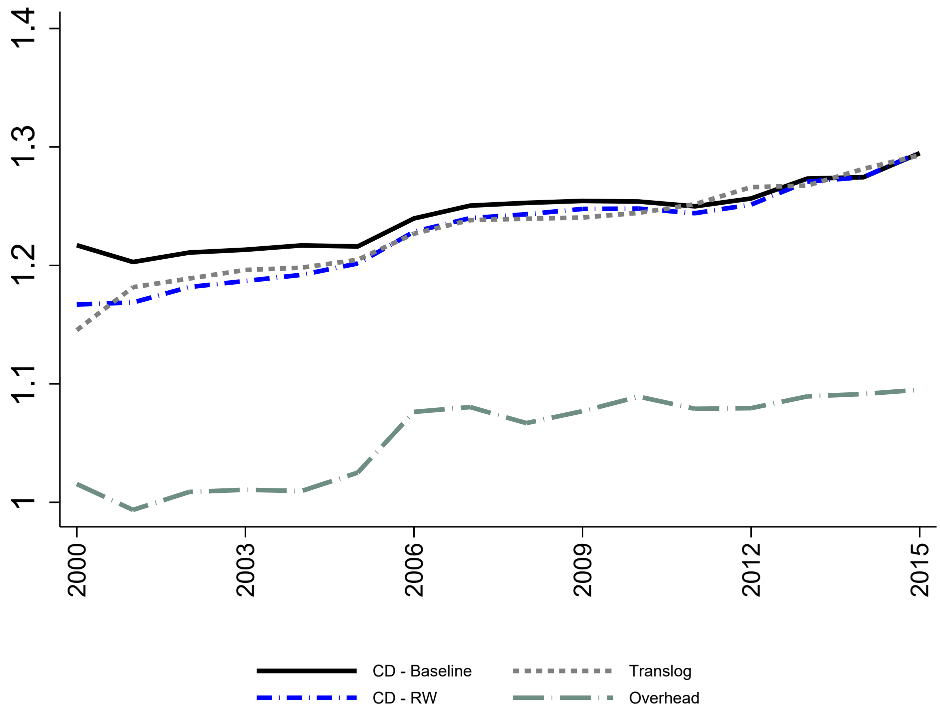
A first possible concern is that the results are driven by technical choices such as the Cobb-Douglas production function specification. To address this concern we re-estimate the average global markup using a translog production function, allowing for more flexibility in the way the inputs are combined to generate output. As shown by the grey-dotted line in Figure 11, the markups from the translog production function are highly correlated with our baseline results, increasing from 1.15 to 1.29 over the 2000–2015 period.

A second plausible concern is that we are implicitly assuming that technologies are constant throughout the period considered. From equation (6), used for the markup calculation, it is clear that if the β is fixed over time so is the technology.[26] This could bias markup trends because changes in expenditure shares translate one to one into markup changes creating an artificial wedge when the production function elasticities are not correctly estimated. To address this concern, we conduct a rolling window estimation. That is, we estimate the production function for 5-year periods and then impute to any given year t the average estimated β's for all years in which t was used for estimation. In this way, we introduce additional flexibility into the estimation by having time-varying β's. The blue-dashed line in Figure 11 shows that the markups from the rolling window estimation are quite similar to those from the baseline estimation. This suggests that, regardless of the assumptions on the variability of technology, we still observe a moderate markup increase in global markets throughout the 2000s.

Another concern is that our baseline markup estimates may be driven by a change in the production technology towards greater fixed (overhead) costs and lower marginal costs. This would imply that the increase in markups could reflect firms recouping their original down payments,

[26] The critique is only valid for the Cobb-Douglas estimation but not for the translog production function since the translog elasticities are firm specific and vary over time (although the underlying parameters are still constant).

Figure 11: Robustness



Notes: The black-solid line reports the baseline markup where β_s^ν is estimated from a Cobb-Douglas production function. The blue-short-dashed line reports the average markup where β_s^ν is time varying and estimated based on a rolling window. The grey-dotted line reports the average markup where β_s^ν is estimated from a translog production function. The teal-long-dashed line reports the average markup where β_s^ν is estimated from a Cobb-Douglas production function that controls for other operating expenses. Markups averaged using firm revenue weights. The figure uses the countries in the baseline sample.

rather than an increase in market power. To address this concern, we re-estimate our production function, explicitly incorporating overhead costs as an additional input.[27] We re-compute markups using the new estimates for the output elasticity of the costs of good sold that control for the effects of overhead costs. We present the results in the teal-dashed line of Figure 11, where we observe that, while the levels are lower, the increase of the average markups remains mostly unchanged by this adjustment. We conclude that technological change associated with shifts in overhead costs plays a small part in the overall *rise* in markups.[28]

A final potential concern is that we estimate the two-digit industry elasticities pooling firm

[27] In Orbis, this corresponds to the variable "Other Operating Expenses" that include for example, sales and marketing expenses, plus administrative expenses and other operating expenses. The number of observations reporting "Other Operating Expenses" corresponds to roughly half of the sample and, therefore, the tail-dashed line in Figure 11 plots the resulting markups for this subsample.

[28] See De Loecker and Eeckhout (2020), Karabarbounis and Neiman (2018), Traina (2018), and Díez et al. (2018) for a similar approach using data on publicly listed firms. Díez et al. (2018) also show that, while the markup level is affected, the *increase* of markups is not affected by the inclusion of overhead costs in the production function.

level observations across countries. To mitigate this concern, we follow De Loecker et al. (2020) and estimate markups using a cost-share approach. In particular, for each firm we compute the share of the variable input (cost of goods sold) in total costs (cost of goods sold plus financial expenses). Then we compute β_s, β_{st} and β_{cst} as the median cost share by sector, sector-year and country-sector-year, respectively. One additional advantage of this approach is that it does not rely on the estimation of a production function and therefore, it is less subject to technical concerns on the identification of the elasticities like those raised by Bond et al. (2020). Appendix Figure B.9 shows the evolution of the average markup if we were to use these output elasticities. As can be seen, there is almost no difference across the three output elasticities but, as in De Loecker et al. (2020), the cost share approach delivers higher average markup levels than the production function estimation approach. However, and most importantly for our analysis, the evolution of markups across all methods is very similar and results in markup increases of around 6%.

8 Conclusion

In this paper we provide new evidence on the recent evolution of market power at the global level. Using detailed data of public and private firms from advanced and emerging countries we estimate markups and find a modest decrease in competition levels around the world. Specifically, we find that average markups increased by about 6% in 2000–2015, significantly below the previous findings in the literature that focused only on listed firms. Further, we also find that the increases are stronger for listed firms and for firms from advanced economies and from service sectors.

However, there is sizable heterogeneity concealed in this average figure. Specifically, we show that the increase is driven by high-markup firms at the top of the markup distribution, whose markups increased by 40% during the sample period. This group includes both listed and private as well as large and small firms, highlighting the importance of working with a sample composed of both types of firms.

Given the predominant role of high-markup firms we explore the relation between firm markup and size and present evidence of a non-monotonic (U-shaped) relationship. That is, we document that markups decrease with firm size until a (large) size threshold is reached, after which we find a positive relation. In addition, we find that most of the increase in markups is explained by markup increases within incumbents and, to a lesser extent, high markups among entrants. These findings could be relevant to understand competition in different markets and to design appropriate policy responses to increases in markups. Inasmuch as higher markups are linked to firms' outcomes like investment, innovation, or the labor share, it is crucial for policymakers to understand recent markups dynamics as well as the significant sources of heterogeneity presented in the paper.

References

Ackerberg, D. A., Caves, K., and Frazer, G. (2015). Identification Properties of Recent Production Function Estimators. *Econometrica*, 83(6):2411–2451.

Akcigit, U., Baslandze, S., and Lotti, F. (2018). Connecting to Power: Political Connections, Innovation, and Firm Dynamics. NBER Working Papers 25136, National Bureau of Economic Research, Inc.

Autor, D., Dorn, D., Katz, L. F., Patterson, C., and Van Reenen, J. (2020). The Fall of the Labor Share and the Rise of Superstar Firms. *The Quarterly Journal of Economics*, 135(2):645–709.

Bajgar, M., Berlingieri, G., Calligaris, S., Criscuolo, C., and Timmis, J. (2019). Industry Concentration in Europe and North America. OECD Productivity Working Papers 18, OECD Publishing.

Baqaee, D. R. and Farhi, E. (2019). Productivity and Misallocation in General Equilibrium. *The Quarterly Journal of Economics*, 135(1):105–163.

Barkai, S. (2020). Declining labor and capital shares. *The Journal of Finance*, 75(5):2421–2463.

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

Baumol, W. (1982). Contestable Markets: an Uprising in the Theory of Industry Structure. *American Economic Review*, 72(1):1–15.

Bond, S., Hashemi, A., Kaplan, G., and Zoch, P. (2020). Some unpleasant markup arithmetic: Production function elasticities and their estimation from production data. Working Paper 27002, National Bureau of Economic Research.

Calligaris, S., Criscuolo, C., and Marcolin, L. (2018). Mark-ups in the Digital Era. OECD Science, Technology and Industry Working Papers, No. 2018/10.

Council of Economic Advisers (2016). Benefits of Competition and Indicators of Market Power. CEA Issue Brief April 2016.

De Loecker, J. and Eeckhout, J. (2017). The Rise of Market Power and the Macroeconomic Implications. Working Papers No. 23687, National Bureau of Economic Research.

De Loecker, J. and Eeckhout, J. (2020). Global Market Power. Working Paper.

De Loecker, J., Eeckhout, J., and Unger, G. (2020). The Rise of Market Power and the Macroeconomic Implications. *The Quarterly Journal of Economics*, 135(2):561–644.

De Loecker, J. and Warzynski, F. (2012). Markups and Firm-Level Export Status. *American Economic Review*, 102(6):2437–2471.

Díez, F., Leigh, D., and Tambunlertchai, S. (2018). Global Market Power and its Macroeconomic Implications. IMF Working Paper No. 18/137.

Edmond, C., Midrigan, V., and Xu, D. Y. (2018). How Costly Are Markups? Working Paper No. 24800, National Bureau of Economic Research.

Eggertsson, G. B., Robbins, J. A., and Wold, E. G. (2018). Kaldor and Pikettys Facts: The Rise of Monopoly Power in the United States. Working Paper No. 24287, National Bureau of Economic Research.

Furman, J. and Orszag, P. (2018). *A Firm-Level Perspective on the Role of Rents in the Rise in Inequality*, pages 19–47. Columbia University Press.

Gal, P. N. (2013). Measuring Total Factor Productivity at the Firm Level using OECD-ORBIS. OECD Economics Department Working Papers 1049, OECD Publishing.

Gopinath, G., Kalemli-Özcan, S., Karabarbounis, L., and Villegas-Sanchez, C. (2017). Capital Allocation and Productivity in South Europe. *The Quarterly Journal of Economics*, 132(4):1915–1967.

Grullon, G., Larkin, Y., and Michaely, R. (2019). Are US Industries Becoming More Concentrated? *Review of Finance*, 23(4):697–743.

Gutiérrez, G. and Philippon, T. (2017). Declining Competition and Investment in the U.S. Working Paper No. 23583, National Bureau of Economic Research.

Gutiérrez, G. and Philippon, T. (2018). How EU Markets Became More Competitive Than US Markets: A Study of Institutional Drift. NBER Working Papers 24700, National Bureau of Economic Research, Inc.

Hall, R. E. (1986). Market Structure and Macroeconomic Fluctuations. *Brookings Papers on Economic Activity*, 17(2):285–338.

Hall, R. E. (1988). The Relation between Price and Marginal Cost in U.S. Industry. *Journal of Political Economy*, 96(5):921–947.

Hall, R. E. (2018). New evidence on the markup of prices over marginal costs and the role of mega-firms in the u.s. economy. Working Paper 24574, National Bureau of Economic Research.

Holmes, T. J. and Stevens, J. J. (2014). An Alternative Theory of the Plant Size Distribution, with Geography and Intra- and International Trade. *Journal of Political Economy*, 122(2):369–421.

Inklaar, R. and Timmer, M. (2013). Using expenditure ppps for sectoral output and productivity comparisons. In *Measuring the Real Size of the World Economy*, pages 617–644. The World Bank, Washington, DC.

Inklaar, R. and Timmer, M. P. (2014). The Relative Price of Services. *Review of Income and Wealth*, 60(4):727–746.

Kalemli-Özcan, S., Sorensen, B., Villegas-Sanchez, C., Volosovych, V., and Yesiltas, S. (2015). How to Construct Nationally Representative Firm Level data from the ORBIS Global Database. Working Paper No. 21558, National Bureau of Economic Research.

Karabarbounis, L. and Neiman, B. (2018). Accounting for Factorless Income. In *NBER Macroeconomics Annual 2018, volume 33*, NBER Chapters. National Bureau of Economic Research, Inc.

Klette, T. J. (1999). Market Power, Scale Economies and Productivity: Estimates from a Panel of Establishment Data. *Journal of Industrial Economics*, 47(4):451–476.

Levinsohn, J. and Petrin, A. (2003). Estimating Production Functions Using Inputs to Control for Unobservables. *The Review of Economic Studies*, 70(2):317–341.

Melitz, M. J. and Polanec, S. (2015). Dynamic Olley-Pakes productivity decomposition with entry and exit. *RAND Journal of Economics*, 46(2):362–375.

Neiman, B. and Vavra, J. S. (2019). The rise of niche consumption. Working Paper 26134, National Bureau of Economic Research.

OECD (2017). Taxonomy of sectors by quartile of digital intensity, 2013-15. Knowledge economies and the digital transformation, OECD Publishing, Paris.

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

Shapiro, C. (2018). Antitrust in a time of populism. *International Journal of Industrial Organization*, 61(C):714–748.

Syverson, C. (2011). What Determines Productivity? *Journal of Economic Literature*, 49(2):326–365.

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

Tirole, J. (1988). *The Theory of Industrial Organization*. MIT Press: Cambridge, MA.

Traina, J. (2018). Is Aggregate Market Power Increasing? Production Trends Using Financial Statements. Technical report, SSRN.

Van Reenen, J. (2018). Increasing Differences Between Firms: Market Power and the Macro-Economy. CEP Discussion Papers dp1576, Centre for Economic Performance, LSE.

Appendix for Online Publication

A Data

The Orbis dataset contains corporate balance sheet information retrieved from the Orbis Historical database, and other characteristics of firms, such as industry classification, date of incorporation, or legal status from the Current Orbis database. We followed the cleaning steps that are based on Kalemli-Özcan et al. (2015), Gopinath et al. (2017) and Gal (2013).

A.1 Duplicates

When there are duplicates found from data downloaded from Orbis, we adopt the following rules. (1) We kept company accounts that are unconsolidated (U1 or U2 in Orbis) or unknown (LF, stands for limited financials). (2) We removed accounts that are duplicates and not "annual report" types. (3) We removed accounts that are duplicates for firms reporting data that refers to less than 12 months of operations. (4) We kept accounts that are duplicates but have the closest reporting date to Dec. 31st in the corresponding year. (5) If there were still duplicates found, we kept those accounts that have more non-missing variables to calculate TFP.

A.2 Data Cleaning

We took two main steps to clean Orbis dataset including cleaning of basic reporting mistakes, and further quality checks on data consistency (see Kalemli-Özcan et al. (2015), Gopinath et al. (2017) and Gal (2013)).

- Cleaning of basic reporting mistakes
  - We dropped firms if they have negative total assets, employment, sales or tangible fixed assets in any year; or if they have more than 2 million employees in any year.
  - We dropped firm-year observations with missing, zero, or negative values for costs of materials, operating revenue and total assets.
  - We dropped firms if they do not have a NACE code.

- We calculated the ratio of the number of employees per million of assets, revenue and revenue/assets. Then we filtered out the top and bottom 0.1 percent of the sample based on these ratios. We did not drop any observations if any of these ratios is missing.

- Further quality checks
  - We constructed a variable on the age of the firm, and dropped those firm-year observations with non-positive age.
  - We dropped firm-year observations if there are non-positive liabilities. We also calculated liabilities by using two different methods and dropped those if the ratio of these methods is greater than 1.1 or smaller than 0.9 to clean reporting errors.
  - We dropped observations if intangible fixed assets are negative, or if fixed assets are zero or negative.
  - We dropped observations with missing costs of employees and the number of employees, as well as those with non-positive costs of employees.
  - We dropped observations with negative values in a set of variables, such as, current liabilities, non-current liabilities, current asset, loans, creditors, other non-current liabilities, long-term debt, shareholder funds, value added, as well as depreciation and amortization.
  - We dropped observations if the ratio of short-term to long-term bank liabilities is greater than 1.1.
  - We further checked some ratios and dropped extreme values as well as winsorized these ratios by dropping the top and bottom 0.1 percent. These ratios include costs of employees to capital, tangible fixed assets to total assets, other shareholder funds to total assets, costs of employees to value added, capital to shareholder funds, and total assets to shareholder funds.
  - We applied filters on the annual growth rates of sales, operating revenues and number of employees to clean "jumps" in the data caused by reporting errors. Different thresholds were applied to firms based on the size of employment. We dropped firms whose annual growth rates were above these thresholds.

- For firms with known (lagged) employment:
  - For firms with 0-10 employees, drop if employment growth is > 1000%
  - For firms with 11-20 employees, drop if employment growth > 500%
  - For firms with 21-50 employees, drop if employment growth is > 300%
  - For firms with 50-100 employees, drop if employment growth is > 200%
  - For firms with 100+ employees, drop if employment growth is > 100%
- For sales and operating revenue we did the same with respect to company tiers by employment but the threshold is twice as large.
- For firms with missing (lagged) employment, we only drop firms when sales (revenue) growth is greater than 2000%.

- We finally removed the very few observations in sectors T "Activities of households as employers; undifferentiated goods–and services–producing activities of household for own use" and U "Activities of Extraterritorial Organizations and Bodies".

A.3 Sectoral Deflators

Since the raw Orbis data is expressed in nominal USD, comparability across countries and time requires not just deflating but also industry-level PPP adjustors; see Calligaris et al. (2018) for another example using this approach and Inklaar and Timmer (2013, 2014) for further details. Following Gopinath et al. (2017), we distinguish between two types of variables. In the case of output, materials and wage bill, these are the steps we follow: (i) we convert the nominal USD variables into local currency using the end-of-period exchange rate from the IFS; (ii) we deflate using country-industry deflators; (iii) we convert back to (real) USD using the Inklar and Timmer industry PPP adjustors. In the case of the capital stock: (i) we convert the nominal USD variables into local currency using the end-of-period exchange rate from the IFS; (ii) we obtain country level deflators for (the price of) investment from the World Bank; (iii) we use country level PPP-adjusted exchange rates to convert back into dollars.

One of the main challenges of this procedure is to find sectoral (2-digit) industry producer price indexes for all countries in our sample. Thus, we compiled information on value added and gross output deflators from various sources, including the OECD, Eurostat and government websites, and used the ones that had better coverage across industries and time. When available we used the 2-digit NACE deflator; this was the case for most sectors in European countries and for manufacturing sectors in most other countries. In the absence of 2-digit deflators we used 1-digit NACE industry deflators and in the absence of disaggregated industry deflators we used the overall country GDP deflator. For consistency, we do not mix sources within a country or over time.

A.4 Data coverage and summary statistics by country

Table A.1: List of Countries in Samples

Baseline Sample		**Alternative Sample**	
Country	*Coverage*	*Country*	*Coverage*
Belgium	2000-2015	Austria	2006-2013
Bulgaria	2002-2015	China	2004-2013
Czech R.	2002-2015	Ireland	2004-2013
Denmark	2000-2015	Slovakia	2004-2013
Estonia	2000-2015	Slovenia	2004-2013
Finland	2000-2015	Hungary	2004-2013
France	2000-2015	Netherlands	2004-2013
Germany	2002-2014	Poland	2004-2013
Great Britain	2000-2015		
Greece	2000-2015		
Italy	2000-2015		
Japan	2000-2015		
Korea	2001-2015		
Latvia	2000-2015		
Portugal	2002-2015		
Romania	2000-2015		
Russia	2002-2015		
Spain	2000-2015		
United States	2000-2015		

Notes: The baseline sample includes countries with financial information for most of the period 2000–2015. The alternative sample includes all countries listed in the table, with the countries from the baseline sample extending over a shorter time span (2004–2013).

Table A.2: Coverage Baseline Sample

	BE	BG*	CZ	DE	DK	EE	ES	FI	FR	GB
2000	53%				47%	39%	59%	58%	51%	76%
2001	49%				53%	49%	60%	64%	50%	81%
2002	62%	81%	34%	28%	54%	64%	59%	58%	52%	66%
2003	61%	97%	45%	30%	56%	81%	48%	61%	55%	66%
2004	64%	94%	49%	33%	56%	79%	49%	51%	54%	65%
2005	68%	92%	48%	44%	61%	62%	59%	52%	55%	60%
2006	68%	134%	51%	46%	65%	69%	58%	54%	54%	53%
2007	68%	157%	52%	45%	83%	94%	56%	57%	53%	55%
2008	72%	145%	53%	47%	85%	68%	51%	58%	56%	67%
2009	64%	128%	51%	45%	80%	40%	47%	55%	52%	57%
2010	67%	125%	52%	47%	78%	44%	49%	54%	52%	62%
2011	71%	141%	55%	50%	86%	64%	48%	58%	58%	65%
2012	69%	162%	56%	51%	86%	70%	48%	57%	57%	69%
2013	69%	166%	55%	52%	80%	70%	49%	56%	56%	64%
2014	70%	148%	56%	47%	84%	60%	49%	56%	55%	66%
2015	67%	161%	48%		86%	46%	42%	55%	47%	66%
	GR	IT	JP	KR	LV	PT	RO*	RU*	US	
2000	29%	36%	24%		45%		60%		16%	
2001	37%	36%	35%	51%	48%		74%		15%	
2002	43%	40%	49%	70%	55%	48%	77%	64%	14%	
2003	44%	37%	57%	70%	54%	50%	80%	68%	14%	
2004	43%	41%	61%	70%	52%	51%	96%	68%	15%	
2005	44%	42%	41%	68%	58%	63%	77%	69%	15%	
2006	45%	46%	39%	66%	61%	69%	86%	72%	28%	
2007	47%	46%	37%	60%	55%	70%	92%	80%	35%	
2008	49%	48%	31%	61%	45%	68%	75%	61%	33%	
2009	43%	45%	34%	61%	39%	67%	83%	73%	34%	
2010	42%	47%	29%	65%	62%	62%	79%	72%	35%	
2011	41%	48%	40%	68%	67%	60%	79%	60%	37%	
2012	40%	47%	74%	68%	69%	59%	93%	73%	37%	
2013	45%	46%	77%	70%	69%	61%	89%	74%	37%	
2014	43%	46%	83%	67%	70%	61%	82%	52%	37%	
2015	35%	47%	69%	65%	69%	62%	90%	63%	35%	

Notes: The table reports the percentage of Orbis firms' output in total output reported by official statistics (OECD). (*) Indicates countries for which the OECD does not report gross output and therefore, we compare to official GDP data. Orbis information is based on the final sample of firms used in the total factor productivity estimation after the cleaning steps described in the appendix. The list of countries: BE (Belgium), BG (Bulgaria), CZ (Czech Republic), DE (Germany), DK (Denmark), EE (Estonia), ES (Spain), FI (Finland), FR (France), GB (United Kingdom), GR (Greece), IT (Italy), JP (Japan), KR (Korea), LV (Latvia), PT (Portugal), RO (Romania), RU (Russia) and US (United States).

Table A.3: Coverage Alternative Sample

	AT	CN*	HU	IE*	NL	PL	SK	SI
2004		62%	40%	137%	43%	24%	27%	59%
2005		71%	47%	105%	23%	22%	37%	61%
2006	34%	103%	28%	123%	28%	30%	39%	63%
2007	37%	118%	53%	136%	33%	33%	38%	63%
2008	46%	108%	60%	169%	28%	36%	34%	62%
2009	44%	90%	63%	179%	47%	33%	39%	61%
2010	56%	25%	63%	178%	52%	34%	40%	74%
2011	59%	115%	65%	162%	67%	34%	45%	77%
2012	58%	91%	66%	156%	72%	31%	44%	78%
2013	51%	108%	64%	210%	82%	31%	42%	77%
2014	50%	51%	65%	189%	77%	32%	43%	78%

Notes: The alternative sample includes all countries in the baseline sample (see table A.2 plus the countries described in this table A.3). The table reports the percentage of Orbis firms' output in total output reported by official statistics (OECD). (*) Indicates countries for which the OECD does not report gross output and therefore, we compare to official GDP data. Orbis information is based on the final sample of firms used in the total factor productivity estimation after the cleaning steps described in the appendix. The list of countries: AT (Austria), CN (China), HU (Hungary), IE (Ireland), NL (Netherlands), PL (Poland), SK (Slovak Republic) and SI (Slovenia).

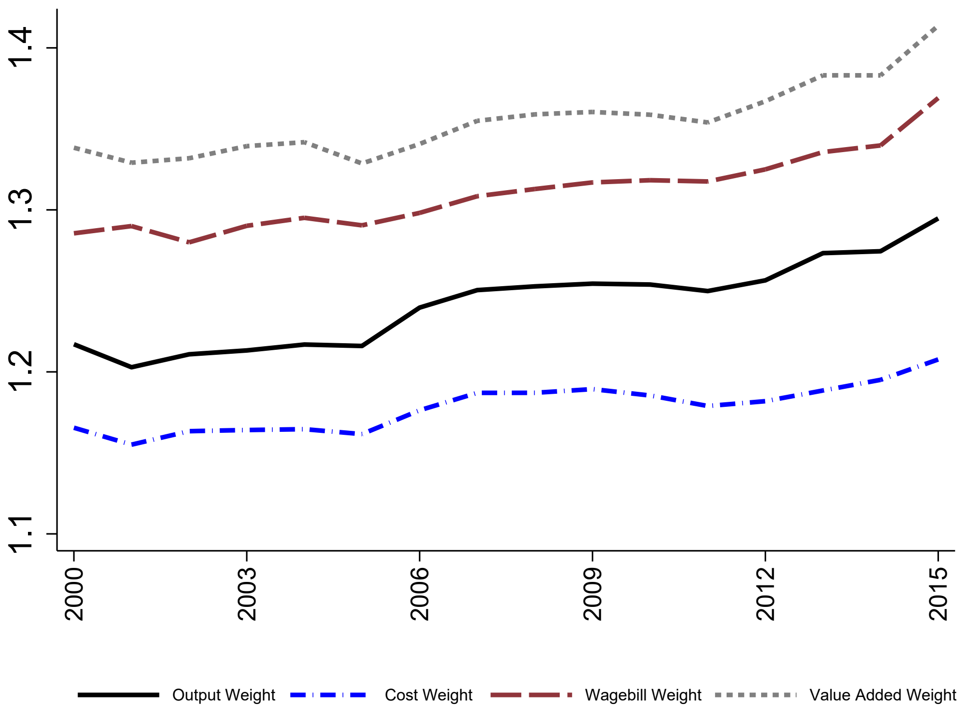
Table A.4: Summary Statistics: By country

Variable	Country	Mean	Standard Deviation	Country	Mean	Standard Deviation	Country	Mean	Standard Deviation
Turnover	BE	84,233,887	696,990,175	FI	38,362,034	260,368,317	LV	7,393,717	31,958,312
Capital		13,979,914	100,549,696		9,465,903	118,840,733		2,548,810	17,861,549
Costs of goods sold		66,386,640	634,216,384		28,155,338	222,811,936		6,058,375	28,228,022
Employment		139	486		105	432		92	305
Turnover	BG	5,556,764	40,580,932	FR	34,182,940	360,655,127	PT	15,165,273	100,828,680
Capital		2,725,264	37,931,498		6,762,753	119,421,970		5,760,218	98,899,458
Costs of goods sold		2,259,318	24,307,486		21,847,800	265,633,456		10,464,551	75,539,576
Employment		87	241		123	1,103		84	454
Turnover	CZ	16,817,568	139,421,029	GB	91,557,023	806,535,176	RO	6,516,149	50,216,177
Capital		7,155,523	112,767,889		22,728,771	314,681,962		3,621,339	59,457,316
Costs of goods sold		11,679,587	111,679,592		69,582,432	662,489,408		4,540,719	39,939,396
Employment		113	448		341	2,700		106	432
Turnover	DE	133,215,889	1,263,108,969	GR	26,543,568	237,944,925	RU	8,056,385	109,058,680
Capital		28,719,088	295,784,120		10,778,044	212,233,939		2,224,698	86,717,078
Costs of goods sold		95,404,392	984,257,536		19,754,360	195,278,016		6,408,362	74,278,272
Employment		402	2,615		87	525		106	640
Turnover	DK	134,335,309	602,333,657	IT	26,079,168	177,235,615	US	2,702,186,216	11,899,058,787
Capital		31,425,800	170,221,438		7,552,751	305,285,571		1,305,098,382	5,887,161,214
Costs of goods sold		94,846,312	425,350,880		17,505,884	138,221,520		1,675,156,480	8,417,844,736
Employment		360	4,517		89	771		8,712	29,644
Turnover	EE	7,502,120	24,837,343	JP	55,695,271	388,209,272			
Capital		3,098,495	28,908,569		15,133,519	327,085,130			
Costs of goods sold		6,017,802	19,990,510		45,135,440	337,030,304			
Employment		68	168		106	591			
Turnover	ES	23,312,825	231,830,222	KR	50,276,999	800,905,883			
Capital		6,873,232	163,918,720		19,680,514	377,397,144			
Costs of goods sold		18,114,374	198,183,552		40,656,552	631,770,368			
Employment		91	730		128	991			

Notes: All monetary variables are expressed in U.S. dollars of 2005. Turnover refers to operating revenue; Capital corresponds to tangible fixed assets; Employment is the number of employees and the variable Costs of goods sold is the direct cost attributable to the production of the goods sold in a company, which includes the cost of the materials used in creating the good along with the direct labor costs used to produce the good. For countries reporting separately material and labor costs, we add these two variables to construct a synthetic costs of goods sold.

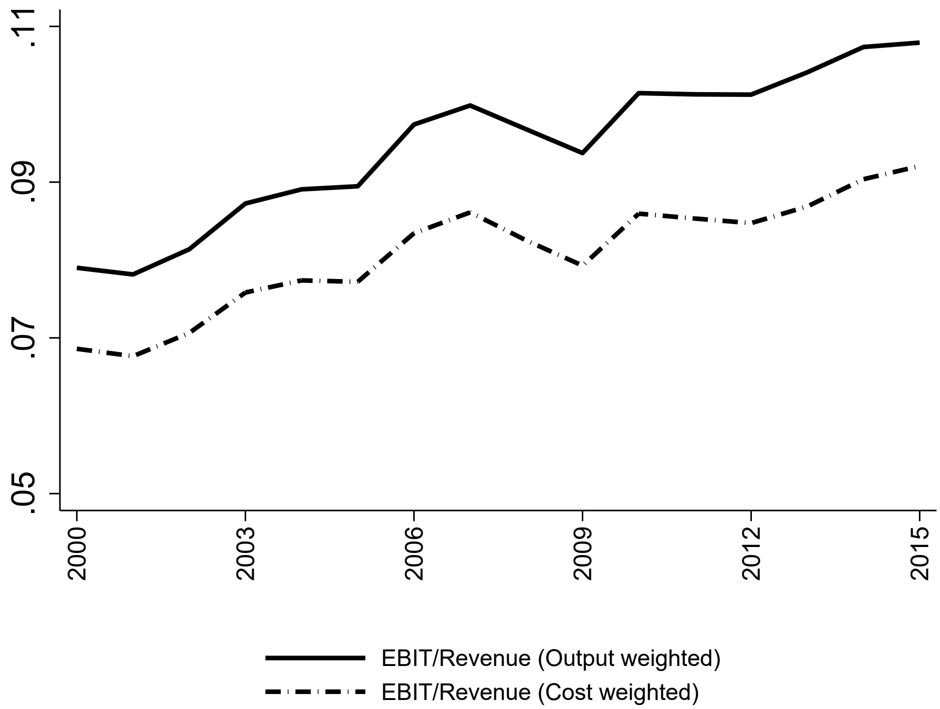
B Additional Results

Figure B.1: Markup Increase by Weighting Scheme



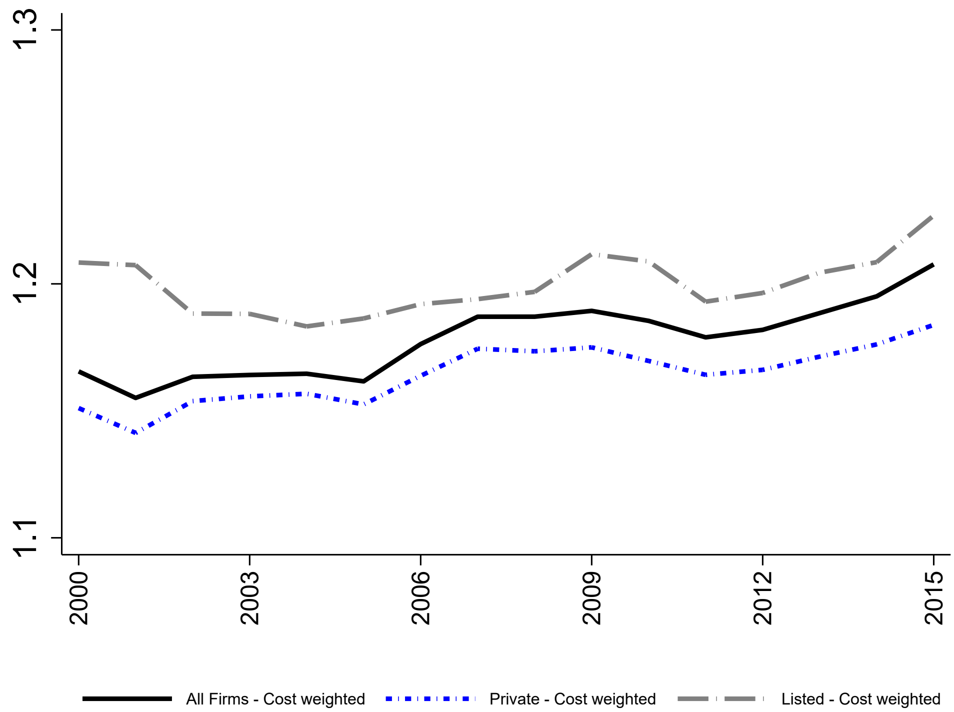
Notes: The figure plots average markups, using alternative firm-level weighting schemes: revenue (black-solid line), value added (gray-dotted line), wage bill (crimson-dashed line), and cost of goods sold (blue-dashdotted line). The figure uses the countries in the baseline sample.

Figure B.2: Increase in Profitability



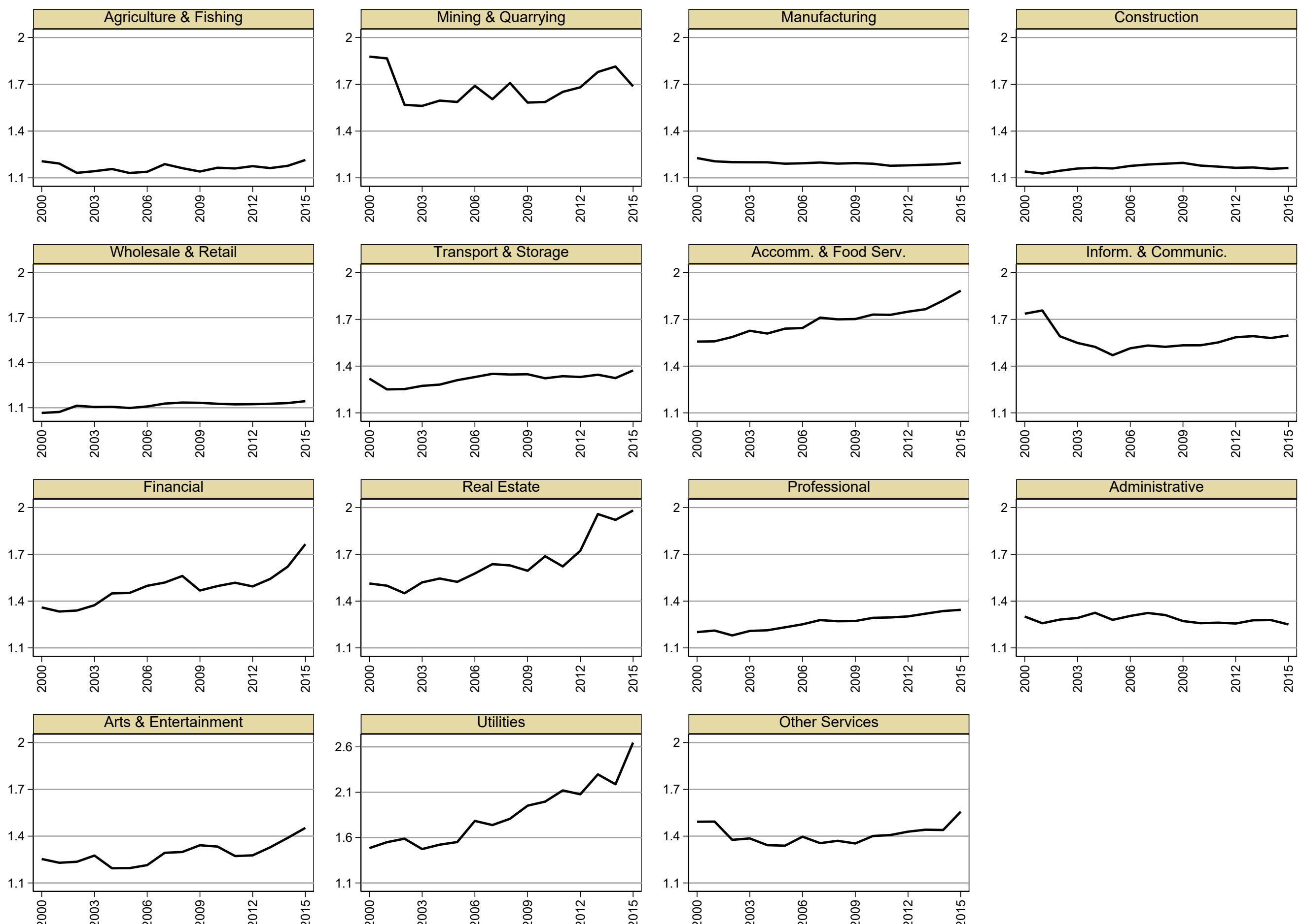
Notes: Firm-level profitability computed as the ratio of EBIT to revenue. Firm-level ratios averaged using revenue weights (solid line) or input costs (COGS) weights (dashdotted line). The figure uses the countries in the baseline sample.

Figure B.3: Average Global Markup – Private vs Listed Firms



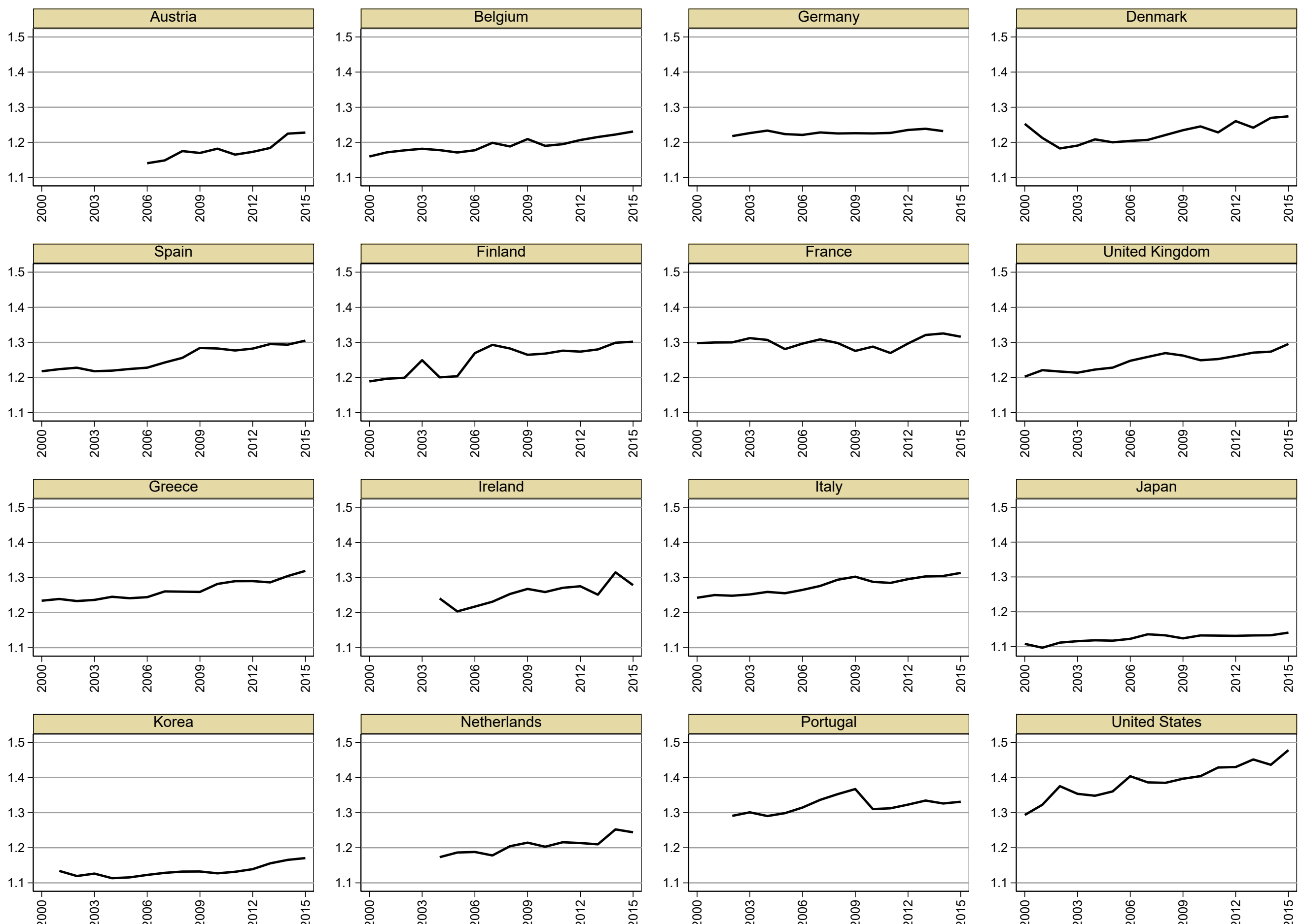
Notes: The black-solid line reports the average markups of all firms; the blue-dashed line reports average markups of private firms; the grey-dashed line reports average markups of listed firms in Orbis. Firm markups are weighted by firms' input costs (COGS). The figure uses the countries in the baseline sample.

Figure B.4: Average Markup by Sector



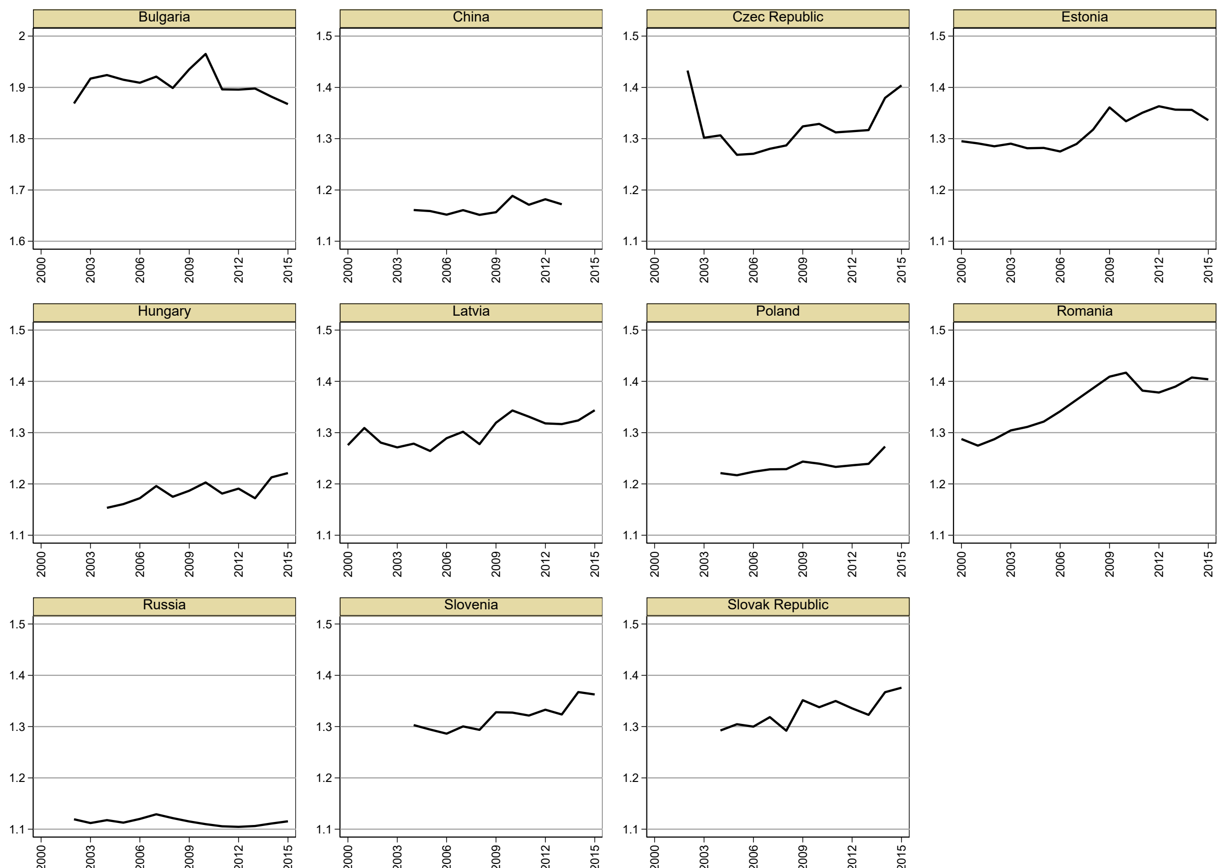
Notes: Each panel plots the average markup in the corresponding sector, weighted by firm revenue. Utilities include NACE sectors D and E. Other services include NACE sectors O, P, Q, and S. The figure uses the countries in the baseline sample.

Figure B.5: Average Markup by Country – Advanced Economies



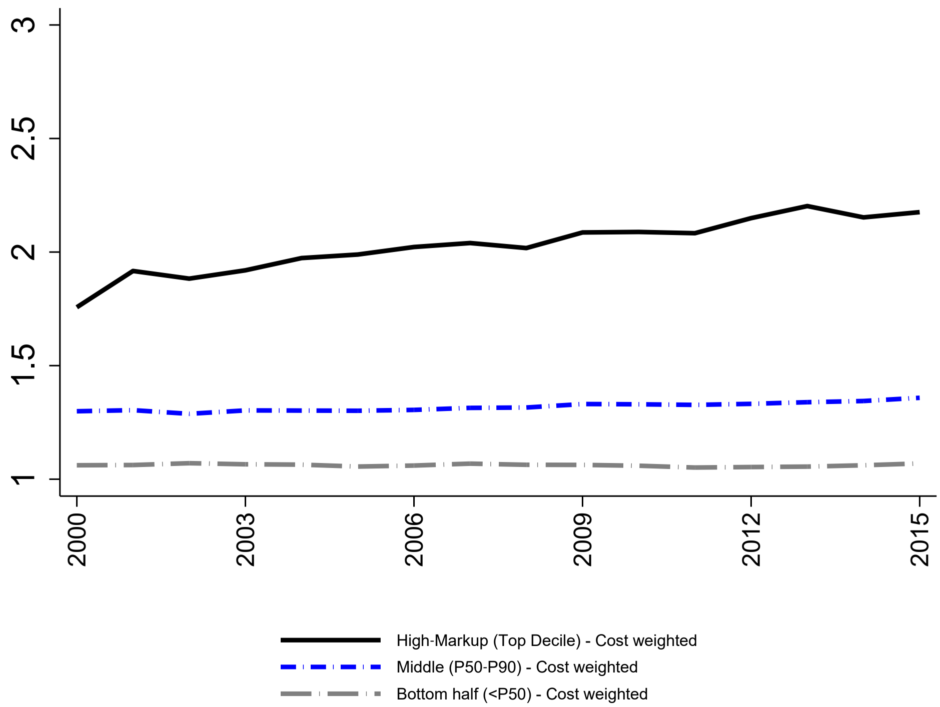
Notes: Each panel plots the average markup in the corresponding country; average markups weighted by firm revenue.

Figure B.6: Average Markup by Country – Emerging Countries



Notes: Each panel plots the average markup in the corresponding country; average markups weighted by firm revenue. Markups in Bulgaria were trimmed at 5 and 95 percentile.

Figure B.7: High-markup, Middle, and Laggard Firms



Notes: High-markup firms are defined as those firms in the upper decile of the markup distribution; middle firms as those between the median and the 90th percentile; bottom half firms are those below the median of the distribution. Firm markups are weighted by the firm's input costs (COGS). The figure uses the countries in the baseline sample.

Figure B.8: Dispersion log(Markup)

Notes: Dispersion is computed as the standard deviation of firm log-markups within a country-four-digit-industry-year and then averaged over time using time invariant value added country-four-digit-industry weights that add up to one. The figure uses the countries in the baseline sample.

Table B.5: Correlation of Firm Profits and Markups

Dependent Variable: Firm Profit (EBIT /Output)

	(1)	(2)	(3)	(4)	(5)	(6)
log *Markup*	0.049***	0.040***	0.024***	0.028***	0.091***	0.092***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
log *Output*					0.030***	0.047***
					(0.000)	(0.000)
log *Overhead*						-0.027***
						(0.000)
Observations	5,684,971	5,684,968	5,578,530	5,559,429	5,559,429	2,569,043
R^2	.018	.079	.59	.62	.63	.66
Firm FE	no	no	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes	yes
Ind FE	no	yes	na	na	na	na
Country-Ind-Year FE	no	no	no	yes	yes	yes
Cluster	id	id	id	id	id	id

Notes: The dependent variable is the ratio of firm profits to firm output (EBIT to Operating Revenue). log *Output* refers to the log of operating revenue. log *Overhead* stands for the log of other operating expenses. Columns (1) and (2) do not include firm fixed effects. Columns (3) to (6) include firm fixed effects. Columns (4) to (6) include country-industry four-digit-year fixed effects. Standard errors are clustered at the firm level are reported in parentheses.

Table B.6: Characteristics of High-Markup Firms

Dependent Variable:

	(1)	(2)	(3)
	$\log TFP$	$\frac{EBIT}{Output}$	$Intangible$
	(1)	(2)	(3)
$High - Markup$	0.177***	0.028***	0.025***
	(0.001)	(0.001)	(0.002)
$\log Output$	0.033***	0.004***	0.055***
	(0.000)	(0.000)	(0.000)
Observations	5,728,674	5,728,265	5,728,674
Country-Ind-Year FE	yes	yes	yes

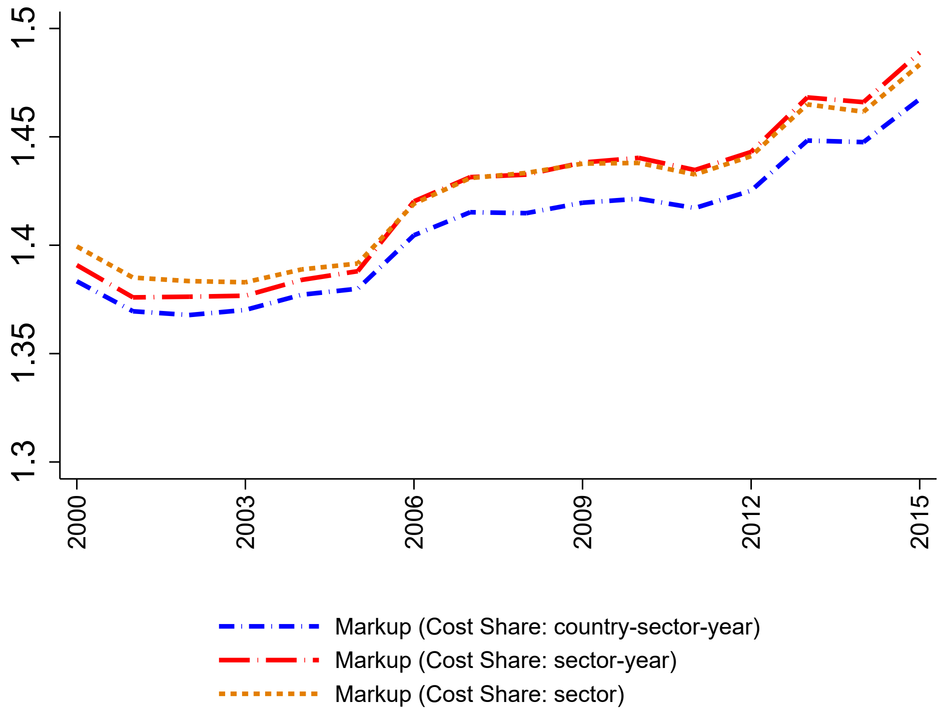
Notes: In column (1) the dependent variable is the log of total factor productivity (TFP). In column (2) the dependent variable is the ratio of EBIT to operating revenue (similar results are found using EBITDA). In column (3) the dependent variable is a dummy variable that takes the variable of one if the company reports expenditure on intangible assets. $High - Markup$ refers to a dummy variable that identifies firms in the top decile of the markup distribution. $\log Output$ refers to the log of operating revenue. All specification control for country-sector four digit-year fixed effects. Standard errors are clustered at the firm level are reported in parentheses.

Table B.7: High-markup firms by Sector

	Share of Firms	**Share of Sales**
Agriculture, forestry and fishing	1%	0.04%
Mining and quarrying	1%	5%
Manufacturing	6%	10%
Electricity, gas, steam and AC	1%	15%
Water supply; sewerage; waste management	4%	2%
Construction	7%	1%
Wholesale and retail trade	14%	2%
Transporting and storage	10%	8%
Accommodation and food service	11%	7%
Information and communication	10%	23%
Financial and insurance activities	4%	9%
Real estate activities	7%	2%
Professional, scientific and technical serv.	8%	5%
Administrative and support services	7%	3%
Education	1%	0.4%
Human health and social work activities	4%	3%
Arts, entertainment and recreation	3%	1%
Other services activities	2%	3%

Notes: High-markup firms are defined as those firms in the upper decile of the markup distribution. Column (1) reports the number of high-markup firms in a sector as share of the total number high-markup firms. Column (2) reports the average revenue of the high-markup firms within a sector as share of total average revenue of high-markup firms. Data refers to the baseline sample.

Figure B.9: Cost Share Based Aggregate Markups



Notes: The dashed and dotted lines (blue, red and orange) report the sales-weighted average markup from output elasticities based on the cost-share approach. In particular, β^{ν}_{csy} is the median by country-sector-year of firms' cost of goods sold share in total cost (cost of goods sold plus financial expenses). β^{ν}_{sy} refers to the median by sector-year and β^{ν}_{s} to the median by sector. The figure uses the countries in the baseline sample.

Table B.8: Markups and Firm Size (Employment): Conditional Correlation

Dependent Variable: log Firm Markup

	(1)	(2)	(3)	(4)	(5)	(6)
	Cross-Section			Within Firm		
$\log L$	-0.044***	-0.135***	-0.083***	-0.079***	-0.154***	-0.073***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
$\log L^2$		0.010***	0.003***		0.011***	0.001***
		(0.000)	(0.000)		(0.000)	(0.000)
$\log TFP$			0.673***			0.903***
			(0.007)			(0.006)
$\log Overhead$			-0.009***			-0.016***
			(0.000)			(0.000)
Observations	5,153,792	5,153,792	2,252,080	5,022,814	5,022,814	2,157,091
Firm FE	no	no	no	yes	yes	yes
Country-Ind-Year FE	yes	yes	yes	yes	yes	yes
Cluster	id	id	id	id	id	id

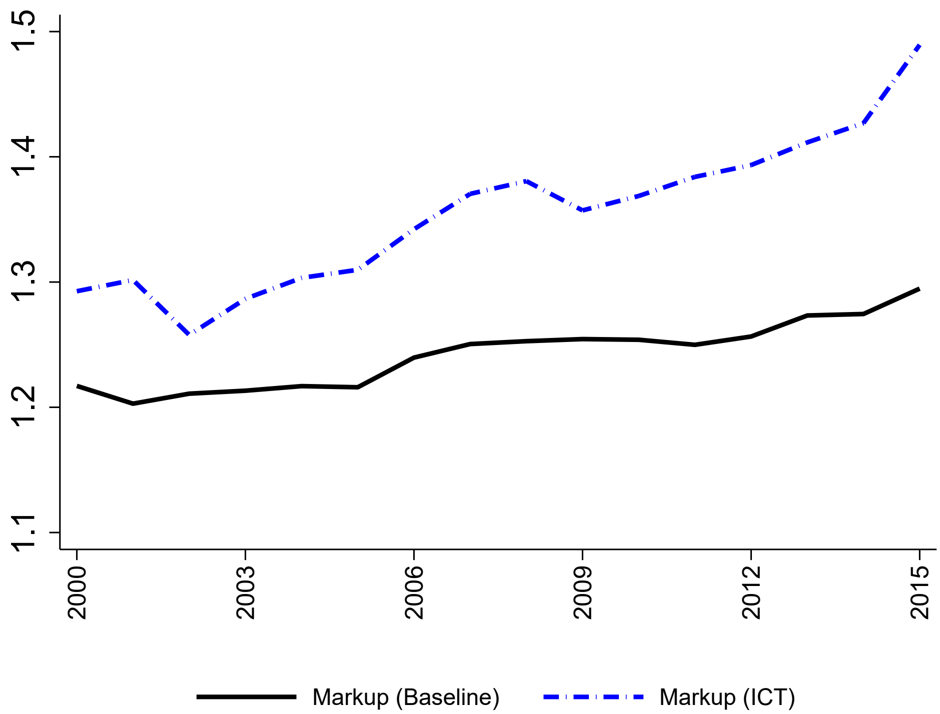
Notes: The dependent variable is the log of firm markup. Firm-level markups are estimated according to equation (6). $\log L$ refers to the log of employment. $\log TFP$ stands for the log of total factor productivity. $\log Overhead$ stands for the log of other operating expenses. Columns (1) to (3) do not include firm fixed effects. Columns (4) to (6) include firm fixed effects. Standard errors are clustered at the firm level are reported in parentheses.

C Digital Economy

The global increase in markups is driven by the high-markup firms in the top decile and these firms are found in all broad economic sectors. At the same time, there is evidence that those sectors from the so-called digital economy have gained market power in recent years; see Calligaris et al. (2018). In light of this, we look at the sectoral decomposition of the markups' dynamics and, in particular, we zoom into the dynamics of those sectors that use more intensively the information and telecommunication technologies (ICT).

We identify those sectors that are ICT intensive *users* by constructing a measure based on OECD (2017) estimates for the digital economy. Specifically, each broad economic sector is sorted into quartiles depending on its ICT usage along several dimensions: software investment, ICT tangible investment, intermediate ICT goods, intermediate ICT services and robot use. We then define a sector as ICT intensive if it is above the median in at least four of these categories. Figure C.1 presents the evolution of markups for the ICT-intensive sectors versus the average. The former indeed present higher-than-average increases in their market power, with average markups increasing twice as much as the overall aggregate—these findings are in line with Calligaris et al. (2018).

Figure C.1: Average Markups, ICT-Intensive vs All firms



Notes: We identify ICT intensity sectors as those that are ICT intensive users by constructing a measure based on OECD (2017) estimates for the digital economy. Specifically, each broad economic sector is sorted into quartiles depending on its ICT usage along several dimensions: software investment, ICT tangible investment, intermediate ICT goods, intermediate ICT services and robot use. We then define a sector as ICT intensive if it is above the median in at least four of these categories. Markups are weighted by firms' revenue. The figure uses the countries in the baseline sample.

D Dynamic OP Decomposition with Entry and Exit

We accommodate the decomposition of aggregate productivity proposed in Melitz and Polanec (2015) to decompose our estimate of aggregate markup computed as the weighted average of firm markup *levels*. This section closely follows the derivations in the appendix of Melitz and Polanec (2015) adapting it to the markup notation. They extend the traditional Olley and Pakes (1996) decomposition:

$$\begin{aligned} M_t &= \sum_i s_{it}\mu_{it} = \bar{\mu_t} + \sum_i (s_{it} - \bar{s_t})(\mu_{it} - \bar{\mu_t}) \\ &= \bar{\mu_t} + cov(s_{it}, \mu_{it}) \end{aligned} \quad \text{D.1}$$

where M_t is the firm sales weighted average markup; s_{it} is the share of firm sales ($P_{it}Y_{it}$) in total sales in the economy ($S_t = \sum_{i,t} P_{it}Y_{it}$); $\bar{\mu}$ is the unweighted average of markups and the second term shows the covariance between firm size (s_{it}) and firm markup (μ_{it}).

The extension accommodates firm entry and exit and preserves the features of the original decomposition in providing an additional decomposition between shifts in the distribution of markups and market share reallocations. Let $s_{Gt} = \sum_{i \in G} s_{it}$ be the aggregate market share of a group G of firms, continuing firms or survivors, entrants and exitors ($G = c, e, x$). The aggregate markup of each period can be expressed as:

$$M_1 = s_{c1}M_{c1} + s_{x1}M_{x1} = M_{c1} + s_{x1}(M_{x1} - M_{c1})$$

$$M_2 = s_{c2}M_{c2} + s_{e2}M_{e2} = M_{c2} + s_{e2}(M_{e2} - M_{c2})$$

The relative change in aggregate markup can be expressed as:

$$\begin{aligned} \frac{M_2 - M_1}{\bar{M}} &= \frac{M_{c2} - M_{c1}}{\bar{M}} + s_{e2}\frac{M_{e2} - M_{c2}}{\bar{M}} + s_{x1}\frac{M_{c1} - M_{x1}}{\bar{M}} \\ &= \frac{1}{1 - \overline{\widetilde{cov}_c}}\frac{\bar{M}_c}{\bar{M}}\left(\frac{\Delta\bar{\mu}_c}{\bar{M}_c} + \Delta\widetilde{cov}_c\right) + s_{e2}\frac{M_{e2} - M_{c2}}{\bar{M}} + s_{x1}\frac{M_{c1} - M_{x1}}{\bar{M}} \end{aligned}$$

where $\widetilde{cov} = cov(s, \mu/M) = cov(s, \mu)/M$ representing the share of aggregate markup M that is driven by the correlation between markups and market shares; $\bar{M} = 1/2(M_1 + M_2)$; $\bar{M}_c = 1/2(M_{c1} + M_{c2})$; $\widetilde{cov}_c = 1/2(\widetilde{cov_{c2}} + \widetilde{cov_{c1}})$ representing time averages over periods 1 and 2. Then it is possible to separate the contribution of the continuing firms into two components, one reflecting shifts in the distribution of firm markups in levels via the change in the unweighted mean $\Delta\bar{\mu_c}$ (within-firm markup changes) and the other reflecting the change in the scale-independent covariance (between-firm markup changes). It is also possible to decompose the contributions of entry and exit in a similar manner:

$$\frac{M_{c1} - M_{x1}}{\bar{M}} = \frac{1}{1 - \overline{\widetilde{cov}_1}} \frac{M_1}{\bar{M}} \left(\frac{\bar{\mu}_{c1} - \bar{\mu}_{x1}}{M_1} + (\widetilde{cov}_{c1} - \widetilde{cov}_{x1}) \right)$$

$$\frac{M_{e2} - M_{c2}}{\bar{M}} = \frac{1}{1 - \overline{\widetilde{cov}_2}} \frac{M_2}{\bar{M}} \left(\frac{\bar{\mu}_{e2} - \bar{\mu}_{c2}}{M_2} + (\widetilde{cov}_{e2} - \widetilde{cov}_{c2}) \right)$$

where $\overline{\widetilde{cov}_1} = s_{x1}\widetilde{cov}_{c1} + (1 - s_{x1})\widetilde{cov}_{x1}$ and $\overline{\widetilde{cov}_2} = s_{e2}\widetilde{cov}_{c2} + (1 - s_{e2})\widetilde{cov}_{e2}$.