Some Thoughts on the Debate about (Aggregate) Markup Measurement*

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Abstract

We stress two main insights from the evidence on the rise of market power. First, markups are different from profit rates to the extent that profits fully account for overhead costs: average markups in the US have risen by 40 points (from 1.21 to 1.61), and profit rates have gone up from 1 to 8% of sales (from 2 to 16% of value added). Second, markups and profits are heterogenous, and increasingly so: the median markup is constant and the upper percentiles are rising sharply. Relying on a representative firm model to draw aggregate conclusions is misleading.

Keywords: *Markups; Market Power; Secular Trends.*

1 Introduction

Since we first circulated our paper *The Rise of Market Power and the Macroeconomic Implications* (De Loecker and Eeckhout (2017)), in August of 2017, we have received an uncountable amount of feedback. The points raised were extremely well taken, and in the revised version of November 2018, we have addressed many of the criticism and incorporated suggestions. There are however also a small number of criticisms that persist and that are heavily cited, even though we believe they are misguided. In an attempt to critically appraise the debate, the *Journal of Economic Perspective (JEP)* commissioned various papers all broadly on the theme of rising markups and its implications. This debate is an excellent opportunity to clarify the strengths

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and weaknesses of the arguments. Unfortunately, in the debate some of the misguided arguments are used to conclude that there is none or mixed evidence of a rise of the aggregate markup.

This note is an attempt to offer our view on these interpretations. For the student of the topic, we want to lay out the arguments that clarify where those contentious conclusions come from, and where we believe the logic fails. Because simplified versions of these arguments are transported to policy – from antitrust enforcement to monetary policy – and corporate interests are large, we hope that our note contributes to a forum where academics and policy makers can make up their own minds without having to rely on those caricatures of the transported underlying arguments.

We classify these contentious arguments into two groups. The first group contains arguments that have misconceptions in measurement and interpretation. The second group contains arguments based on aggregation, and whether the logic implicitly assumes a representative firm. Firm heterogeneity and the change in the distribution of firms over time are at the heart of the logic that explains the rise in market power. Current time academics have fully embraced that representative agent economics does not always provide the correct insights about many economic phenomena. Modern economic analysis (in IO, macro, labor,...) has developed tools to work with rich heterogeneity. If the dust settles on this debate and there is a consensus about what has happened to market power – or at least, when there is agreement to disagree – we are convinced that one issue will not be contentious at all: that we cannot understand the determinants of market power nor its evolution without heterogeneous firms. A representative firm framework is counterfactual, and it leads to incorrect conclusions on the presence of market power.

2 Measurement and Methodology

First, a number of misinterpretations of the markup measures are voiced repeatedly. People refer to alternative measures of markups that have risen far less. In particular, the paper by James Traina (2018) finds an increase of 8-10 percentage points between 1980 and 2016. The main difference in magnitude of his increase with our reported increase is due to the omission of an important cost variable, overhead or so-called SG&A, after the accounting term "Selling, General and Administrative Expenses".

In our markup estimation, we do incorporate SG&A (either as an input in production or as a fixed cost), but we do not consider it to adjust instantaneously.[1] The confusion about the difference between James Traina (2018)'s and our work and those who use his argument stems from the fact that his measure corresponds very closely to the profit rate whereas ours is a measure of the markup as traditionally defined in IO. There is a crucial distinction between inputs that are variable and those that are not, or simply a distinction between variable and

[1] In the first draft of this note, we were mistaken about the time line of the use of SG&A in analyzing market power. Traina (2018)'s work on SG&A and ours were conducted simultaneously and independently. He has not copied our analysis of the role of SG&A as we mistakenly claimed initially. We are grateful to James for sharing his insights. They have shaped our understanding of the issue.

fixed costs. In addition, the presence of adjustment costs and other frictions turns these inputs into so-called dynamic inputs. The cost-based method that we use still applies to measure markups from the firm's cost minimization decision. However, the first order condition now is no longer static but dynamic, and takes into account those frictions.

Let us be clear, we do not claim to have the perfect measurement of markups and of market power; we simply want to point out the potential weaknesses in some of the arguments that are used to show that there has been no rise in market power. We show that underlying the disagreement are a set of assumptions on which the IO literature and the micro-productivity literature has a lot to say.

MARKUPS OR PROFIT RATES? Let us now list all the assumptions James Traina (2018)'s measure rests on to obtain his results on markups. First, he sums all inputs except physical capital, hereby implicitly assuming that COGS and all factors captured by SG&A are perfect substitutes. Taken to the extreme, this implies that Amazon could keep sales constant, by substituting all products with marketing expenses; and Coca Cola could produce soft drinks without water and sugar, but instead increase advertising. Second, he assumes that all these inputs are perfectly variable and optimized statically period by period. We believe firms face substantial adjustment costs when engaging in R&D, advertising, marketing, etc., which is a continuous process with a substantial forward-looking component. Third, he estimates a production function to obtain the output elasticity θ^{V+X}. Adding all the assumptions together yields the following expression for his measure τ:

$$\tau_{it} = \theta^{V+X} \frac{S_{it}}{P_{it}^{V} V_{it} + P_{it}^{X} X_{it}}, \tag{1}$$

where $p^V V$ is the expenditure on the variable input, $p^X X$ is the expenditure on overhead as measured by SG&A and where $\theta^{V+X} \approx 0.95$ (though he estimates a separate elasticity for each sector). We are reluctant to call this a markup (hence the notation $\tau \neq \mu$), since it does not measure the price-to-marginal cost ratio. Instead, by collapsing all but capital into one input, this measure relies on the ratio of sales to operating expenses (OPX).

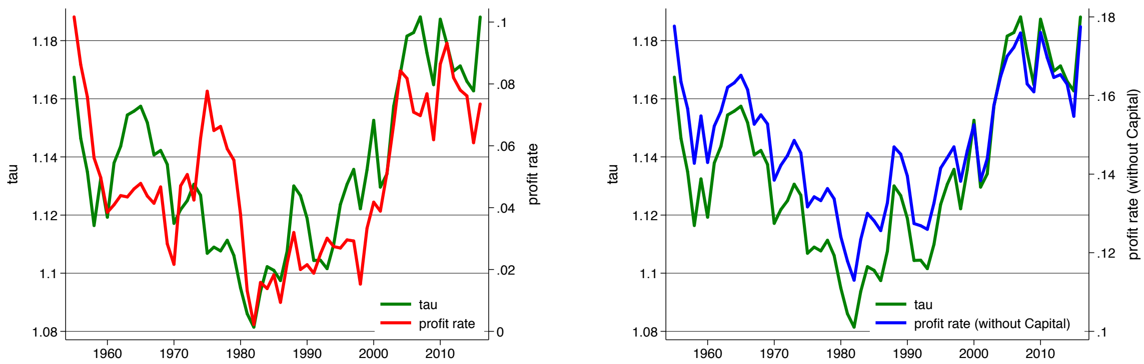
This ratio is in turn directly related to the operation profit rate, the definition of which is

$$\pi_{it}^{OPX} = \frac{S_{it} - P_{it}^{V} V_{it} - P_{it}^{X} X_{it}}{S_{it}} = 1 - \frac{P_{it}^{V} V_{it} + P_{it}^{X} X_{it}}{S_{it}}. \tag{2}$$

We can therefore write the measure τ_{it} as

$$\tau_{it} = \theta^{V+X} \frac{1}{1 - \pi_{it}^{OPX}}. \tag{3}$$

Given this identity, it is not surprising that this measure is closely related to the average profit rate excluding capital that we report π_{it}^{OPX} (Figure 6.1 in the Online Appendix of De Loecker, Eeckhout, and Unger (2018)) up to a level difference, which is in turn similar the evolution of the profit rate including capital, π_{it} (Figure 14.a). An increase in π^{OPX} leads to an increase in τ. There is a level difference, with τ just above 1 and π just above zero. After aggregating over all firms, the average τ_t and the average profit rates are plotted in Figure 1.[2] These measures for profit rates and τ are not identical because of aggregation, but their evolution is very close.



(a) π_t (b) π_t^{OPX}

Figure 1: τ versus Profit Rates

We find an increase in both profit rates between 1980 and 2016 of about 7-8 percentage points, and for the measure τ, which we interpret as an alternative measure of the profit rate, we see an increase of about 10 points, from 1.08 to 1.18. Compare this to our measures of the markup that has increased by 30-40 points (depending on the specification). The main insight for the user of markups in economic analysis is that markups and profit margins are not identical, even though in many simple models they are. Their difference gives us different insights. The fact that the profit rate has increased less than markups is evidence that fixed costs (SG&A) have gone up. The rise in fixed costs partially offsets the rise in markups. Firms that charge higher markups do so in part because they need to cover higher fixed costs. However, the markup increase outpaces the rise in fixed costs leading to a rise in profit rates (and in the measure τ). This indicates that there is a fundamental change in technology. Firms incur higher fixed costs (hence a sharp increase in markups), but this in turn leads to lower competition and hence higher profits.[3]

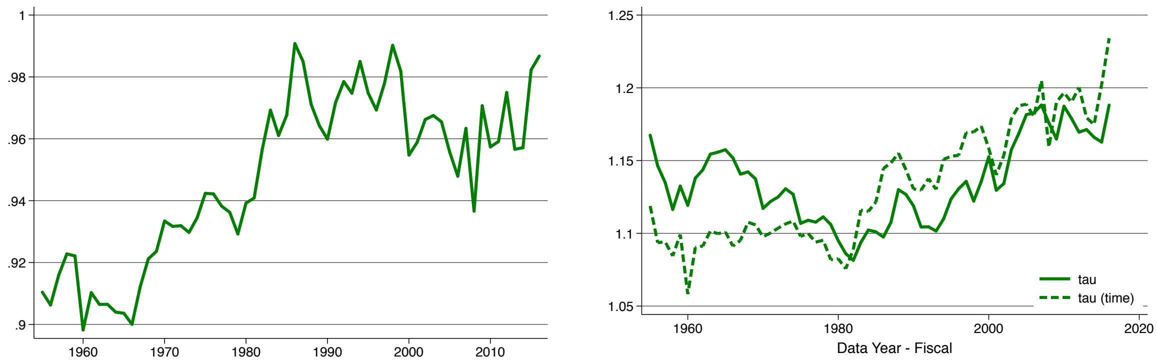
τ_t WITH TIME-VARYING TECHNOLOGY. So far, we have reported the measure for τ where the output elasticity is constant over time (and varying by sector) as reported by James Traina (2018). In De Loecker, Eeckhout, and Unger (2018) we find evidence of increasing returns to scale and that the returns to change over time. In the Cobb-Douglas technology that we consider with inputs V, K, X, the returns to scale are given by the sum of the output elasticities $\theta^V + \theta^X + \theta^K$. We find that this measure of returns to scale increases from above 1.05 to 1.20 and then decreases again (see Figure 5.a in De Loecker, Eeckhout, and Unger (2018)). Moreover,

[2] All evidence we show is for the COMPUSTAT sample of publicly traded firms.

[3] We find that the increase in SG&A is highest for those firms with the highest profits (Figure 16 in De Loecker, Eeckhout, and Unger (2018)).

we know that θ^V has slightly declined and that θ^X has substantially increased. The latter is responsible for the increase in returns to scale. There may thus be a non-trivial time variation in θ^{V+X} as well.

If we estimate a production function with inputs $V + X$ and K, where we explicitly allow the technology to be time-varying, then we obtain the following elasticity θ^{V+X}, reported in Figure 2a.[4]



(a) Estimated θ_t^{V+X}

(b) Evolution of τ_t with time-varying θ_t^{V+X}

Figure 2: Time-varying technology.

We find that the output elasticity of the bundle $V + X$ has gone from 0.90 early in the period to 0.98 in recent years. This is evidence of technological change: overhead (SG&A) is increasingly important and seems to be the driver of the change in returns to scale. As a result of this technological change, the implied measure τ with time-varying output elasticities reported in Figure 2b (dashed line) has increased more than the measure with a time-invariant elasticity. In 1980 this measure starts at 1.08 and rises to 1.23 in 2016, an increase of 15 points, compared to the increase of 10 points when the technology is held constant. It indicates that there is an important role for technological change in understanding market power. To be clear, this does not change by how much the profit rate has gone up (8 percentage points),[5] but it tells us that there has been a substantial change in the technology which leads firms to have a higher ratio of price to cost.

Let us reiterate though that even accounting for time-varying technology, τ is not an adequate measure of markups. It assumes that overhead costs (SG&A) adjust flexibly, and that they are prefect substitutes with the traditional variable inputs in COGS. We find conclusive evidence that these assumptions do not hold (see Figure 20 in De Loecker, Eeckhout, and Unger (2018)). Therefore τ is not an adequate measure of price to marginal cost.

[4]We obtain the production function estimates using a simple OLS regression with industry effects but without accounting for endogeneity. The main challenge is the estimation of the output elasticity θ^V. But in this note we do not want to reiterate on all the intricacies of estimating production functions, rather we want to focus on the underlying technology, and the characteristics of the various inputs.

[5]In fact, since now also the elasticity is time-varying, the evolution of τ no longer maps directly into the profit rate as it did when the elasticity was constant.

USING DIFFERENT VARIABLE INPUTS TO CORROBORATE ESTIMATES. We do think it is a good idea to subject the markup estimation to robustness regarding which inputs can be thought of as variable. If all inputs are truly variable and if input choices face no dynamic considerations, all inputs should yield identical markup patterns. At a minimum we will have gotten rid of the unappealing assumption that *all* inputs of production are perfect substitutes in production. We did exactly this for the Compustat sample and found that the implied markups using either capital or SG&A are dramatically different from the markup obtained with COGS: the levels are not plausible, and the time-series pattern is quite distinct.

We can go even further. Our own measure for markups uses COGS which is a bundle of inputs with many different characteristics. Though data availability is poor, for a small subsample we can verify robustness of our measure to using only one input of the bundle contained in COGS, namely wages. We find similar patterns for markups.

The bottom-line is thus that the production approach does not require to measure all relevant input costs, or even all the variable ones. It merely requires to consider *one* and multiply its observed inverse-revenue-share with the correct output elasticity of that *one* variable input. This is precisely why we went at great length to consider various specifications of the production function, with an important one being the production function with overhead costs as a factor of production.

All three inputs, cost of goods sold, capital and SG&A, potentially contain variable, quasi-fixed and fixed components; and again correctly applying the production approach can help discriminate the fixedness of these inputs by comparing implied markups obtained input-by-input, rather than summing all inputs together to measure variable profit margins.

3 Aggregation of Heterogeneous Firms

Another persistent misrepresentation of our approach and results is the presumption that markups have increased for all firms. Implications of the rise of markups are obtained assuming aggregation in the presence of homogeneous firms. There are three distinct, but related, issues we would like to clarify. Each of these issues is centered around the innate heterogeneity in markups across firms, both within industries and across the entire economy.

To set the stage, recall that possibly the most important of our findings is that median markups have not changed and that the rise in markup is driven entirely by the upper percentiles (see Figure 2 in De Loecker and Eeckhout (2017)). Most firms see no increase in markups, and a few select firms have huge rises.

AGGREGATE DATA. Let us start by clarifying why subsequent work (e.g. Hall (2018)) that relies on aggregate data (industry level or economy-wide) find increasing markups but to a lesser extent. To make the comparison as simple as possible, let us abstract from any technological change or sectoral-heterogeneity in output elasticities and simply keep θ constant throughout.

Let us compare our aggregate markup with the one obtained using aggregate data:

$$\sum_i m_{it} \frac{S_{it}}{P_{it}^V V_{it}} \neq \frac{\sum_i S_{it}}{\sum_i P_{it}^V V_{it}} \tag{4}$$

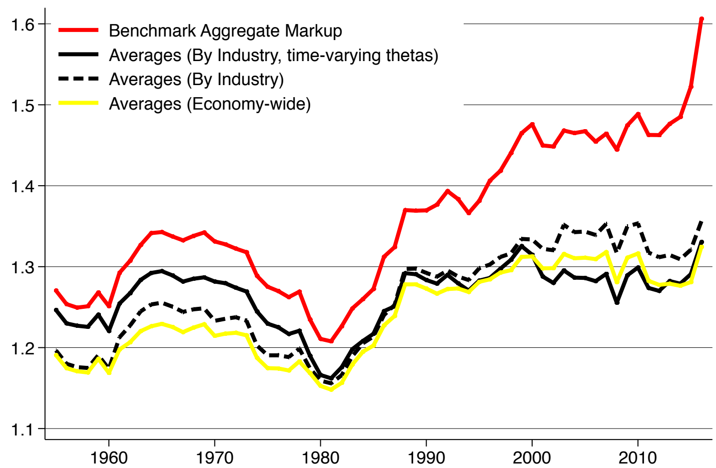


Figure 3: Using Industry and Economy-wide Averages versus Aggregating Micro Data

The simple reason that the two objects are not equal to each other is due to the heterogeneity in markups across firms.[6] This is the case for any cross-section, i.e. a year, in the data; but importantly with the reported increasing skewness in the underlying markup distribution, this difference becomes larger over time. The widening gap between the micro and the macro ratios is simple economics: if market share is reallocating towards the higher markup firms, this reinforces the process of increased skewness, due to the increased correlation of markups and market share (in a given industry or in the entire economy depending on the focus). This is a result we made available in De Loecker and Eeckhout (2017); in Appendix Figure B.5 we plot our aggregate markup series (share-weighted) against the aggregate version of Compustat (as well as an aggregate obtained from the IRS data); and we confirm this observation. We reproduce the Figure here (Figure 3), and we compare the share-weighted aggregate markup (in red) to one where we aggregate across all firms (economy-wide, in yellow); and one where we first aggregate by sectors and then apply sectoral-weights (dashed, in black) closer to a recent working paper of Hall (2018) for example; and one were we do the same but with sector and time-varying elasticities (in black).

It is clear from the figure that the aggregate-based series trend up but to a much lesser extent and this is to be expected given the increased dispersion. This tells us that the dispersion and skewness of the distribution has increased over time. Most of the rise that we observe in the average markup disappears once we use industry or economy-wide averages. This tells us that most of the heterogeneity in markups is within industry and that the reallocation of market shares (see also below) occurs mainly within industries.

[6]With identical firms the market share is $m_{ij} = N^{-1}$ and both ratio's are identical.

EXCESSIVE IMPLIED PROFIT RATES IN A REPRESENTATIVE FIRM ECONOMY. When one takes our share-weighted aggregate markups ($\sum_i m_i\mu_i$) to draw implications for the aggregate profit share, the implied profit rates are completely unrealistic. Recall, we see a rise in markups of about 40 points and a rise in profit rates of 8 percentage points.

Syverson (2018) and Basu (2018) argue that the implied profit rate given our markup estimates is excessive. From the definition of the profits, derive the following identity between the profit rate and markups, where $C(Q)$ is the total cost function:[7]

$$\pi_{it} = \frac{P_{it}Q_{it} - C(Q_{it})}{P_{it}Q_{it}} = 1 - \frac{AC_{it}}{\mu_{it}MC_{it}}, \tag{5}$$

where $\frac{AC_{it}}{MC_{it}}$ is the ratio of average cost to marginal cost. We can rewrite this equation as

$$\mu_{it} = \frac{1}{1-\pi_{it}}\frac{AC_{it}}{MC_{it}}, \tag{6}$$

and if we interpret the data through the lens of a representative firm economy, then we can back out the implied aggregate profit rate (assuming no time variation in the ratio of average cost over marginal cost). For example, consider the ratio of equation (6) evaluated in 1980 and in 2016, and let the profit rate $\pi_{1980} = 0$ (which is close to the profit rate of 1% we find), then:

$$\frac{1.61}{1.21} = \frac{1}{1-\pi_{2016}} \quad \Rightarrow \quad \pi_{2016} = 25\% \tag{7}$$

This leads to a profit rate of 25%, which is roughly 50% of GDP (because gross output is about twice GDP). This is completely unrealistic, especially since in our sample we find a profit rate of around 8% in 2016 (approximately 16% of value added).

Syverson (2018) and Basu (2018) argue that these unrealistic implied profit rates are evidence that there is a problem with the markup estimates. We show that two assumptions in this logic are unrealistic, and that once we correct for these assumptions, equation (6) (and therefore equation (5)) does indeed hold. The first assumption on which their logic is based is that the ratio $\frac{AC_{it}}{MC_{it}}$ is independent of the overhead cost. The second assumption they use to come to this conclusion is that all firms are identical and there is a representative firm economy. Both assumptions are counterfactual and therefore unrealistic. In what follows, we adjust for these assumptions, and derive again the implied profit rates and verify whether they remain unrealistic.

Consider a technology with variable input V and capital K, and fixed cost F. Then we can write the cost function as $C(Q_{it}) = c(Q_{it}) - F_{it}$. The Right hand side in equation (5) is given by:

$$1 - \frac{AC_{it}}{\mu_{it}MC_{it}} = 1 - \frac{\frac{c(Q_{it})}{Q_{it}} - \frac{F_{it}}{Q_{it}}}{\mu_{it}c'(Q_{it})}. \tag{8}$$

If in addition we assume Cobb-Douglas where $Q_{it} = \Omega_{it}V_{it}^{\theta^V}K_{it}^{\theta^K}$, where Ω_{it} is the firm's TFP, then his corresponds to the technology we estimated in the paper and that gave rise to our

[7] This relation holds for any cost minimizing firm with a well behaved technology $C(Q)$ and requires no further assumptions

benchmark markup estimates. Conventional algebra establishes that $C(Q_{it}) = \Gamma_{it} Q_{it}^{1/\gamma_{it}}$ where $\gamma_{it} = \theta_{it}^V + \theta_{it}^K$ and Γ_{it} is a constant. Then, since $P = \mu MC$ and $PQ = S$, it follows that:

$$\pi_{it} = 1 - \frac{\gamma_{it}}{\mu_{it}} - \frac{F_{it}}{S_{it}}. \tag{9}$$

First, the ratio of average to marginal costs must include the overhead cost F_{it}. This was missing in the calculation in Syverson (2018) and Basu (2018). Second, we aggregate over heterogeneous firms, and we know that between 1980 and 2016 the dispersion in markups and firm size has gone up: the upper percentiles have risen sharply while the median has remained constant. This is the main driver behind the rise in average market power. We also expect that the aggregation of equation (9) will have increasingly differential impact on the relation between the average profit rate (LHS) and the aggregated version of the right hand side. We can write the aggregation of this equation as:[8]

$$\pi_t = \sum_i m_{it}\pi_{it} = 1 - \sum_i m_{it}\frac{\gamma_{it}}{\mu_{it}} - \frac{F_t}{S_t}. \tag{10}$$

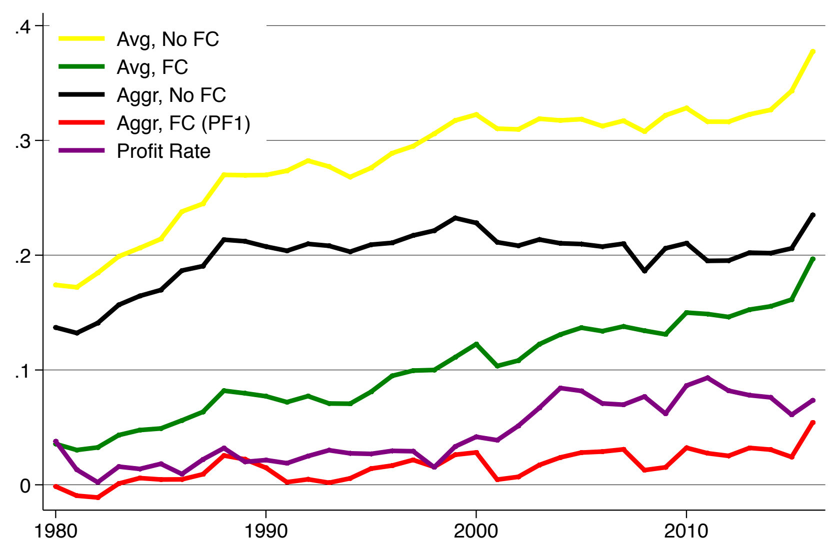


Figure 4: Decomposition of Equation (9) due to Overhead Costs and Aggregation.

In Figure 4, we plot the average profit rate (in purple) from the data between 1980 and 2016 without any assumption on technology or markups against measures of the RHS under different assumptions. We also report the numerical values for the two years in Table 1. Because the change in γ_t is modest, we keep it constant at 1 as these authors do. For the different versions of the RHS, first, in yellow we plot $1 - \frac{1}{\mu_t}$ as proposed by Syverson (2018) and Basu (2018), assuming no fixed cost (constant returns to scale) using average markups (no aggregation). This

[8]The last term follows from $\sum_i m_{it}\frac{F_{it}}{S_{it}} = \sum_i \frac{S_{it}}{S_t}\frac{F_{it}}{S_{it}} = \frac{F_t}{S_t}$.

		1980	2016
Use Average	No Fixed Cost	0.17	0.38
Use Average	Fixed Cost	0.04	0.20
Aggregation	No Fixed Cost	0.14	0.24
Aggregation	Fixed Cost	0.00	0.05

Table 1: Decomposition of the average profit rate from equation (9).

indeed leads to a profit rate of 38%. Note that under these assumptions, even in 1980 the profit rate was already 17%.

Second, in green we plot the right hand side taking into account fixed costs F as measured by SG&A as a share of sales: $1 - \frac{1}{\mu_t} - \frac{F_t}{S_t}$. Not surprisingly, accounting for returns to scale substantially lowers the RHS. In 1980 this measure is 0.04 and in 2016 it is 0.20. Still, this measure rises substantially above the average profit rate (in purple) as measured in the data.

Third, while not accounting for fixed costs, we properly aggregate markups: $1 - \sum_i m_{it} \frac{\gamma_{it}}{\mu_{it}}$. From Jensen's inequality, for any non-linear function the sum of the averages is not equal to the average of the sum. Moreover, we know that the distribution of sales and therefore of sales shares m_{it} has become more skewed over this period, so we expect the error of not using a proper aggregation to compound into bigger deviations. This is plotted in black. This measure rises from 0.14 to 0.24.

Finally, in red we plot the RHS exactly as it is written in equation (10), accounting both for the fixed cost and for the aggregation. This is basically the combination of the green and the black line. This measure goes from 0.00 to 0.05. If anything, the profits predicted by the RHS that uses our markup estimate is lower than what we find for the average profit rate that reaches 7% in 2016. In order to match the profits exactly, we would need even higher estimated markups μ_{it}.

Overall, the relation that predicts average profit rates as a function of markups remarkably fits the data once we properly account for returns to scale (fixed costs) and once we we properly aggregate. This indicates that our measure of markups does not predict an outlandish profit rate. What it does confirm is that markups and profit rates are different objects and that we should be careful comparing them. Too often, they are used interchangeably.

In the Appendix we also report the same exercise for a production technology where overhead (SG&A) is treated as a factor of production, not as a fixed cost. Then output is written as $F(V, K, X) = \Omega V^{\theta^V} K^{\theta^K} X^{\theta^X}$. Without a fixed cost, the returns to scale are exclusively captured by $\gamma = \theta^V + \theta^K + \theta^X$.[9] We find very similar patterns. There, the role of aggregation is more important and the role of accounting for returns to scale is less so. Remarkably, properly accounting for scale returns and aggregation gives very similar predictions for both technologies, PF1 where overhead is a fixed cost and PF2 where overhead is a factor of production. In the Appendix we also report the decomposition for the whole sample period for both technologies.

[9] Note that in the decomposition exercise above we have set $\gamma = 1$ because this is close to what we have estimated and because the lion share of the returns to scale stems from the fixed cost, not from the change in the estimated coefficients $\theta^V + \theta^K$.

EXTERNAL EVIDENCE: REALLOCATION. One of the main insights of the rise in average weighted markups is that the rise does not exclusively come from an increase in the markup itself. When we decompose the change in markups we find that about one third of the increase is due to an increase in the markup within firms, mainly a fattening of the upper tail of the distribution. However, a substantial share of the increase in average weighted markups is due to the reallocation of market share from low to high markup firms. In fact, average weighted markups could have increased even if there was no increase at all in the markup distribution and there had only been reallocation of market share.

The evidence of reallocation is not exclusive to our work. It has been confirmed over and over in several other papers. In their analysis of superstar firms, Autor, Dorn, Katz, Patterson, and Van Reenen (2017) (see also Hartman-Glaser, Lustig, and Zhang (2016)) show an increase of the market share of firms that are in highly concentrated industries. Similarly, in their work on the transmission of micro-level shocks in a model with input-output interlinkages between firms and sectors, Baqaee and Farhi (2017) show that over half of the output distortions from markups are due to the reallocation of market share to high markup firms. And even though in their study of the evolution of the Herfindahl-Hirschman Index (HHI) of concentration as a measure of market power, Gutiérrez and Philippon (2017), Grullon, Larkin, and Michaely (2016) and Brennan (2016) do not explicitly focus on the rising market share, the change in their HHI measures is obviously not driven by a degenerate distribution of representative firms, but rather by a distribution marked by reallocation. All these studies confirm that reallocation towards high markup firms is quantitatively important.

Instead, when envisaging a representative firm economy, there can be no effect on markups from reallocation at all. Any reallocation from one firm to another is between identical firms and thus cannot account for a change in the average weighted markup. The evidence in the literature overwhelmingly points towards an important role for reallocation. This calls for a conclusive rejection of the representative firm framework.

INPUT WEIGHTING. The baseline measure of average markups we have presented is weighted with market share weights. Already in the first draft we also included input weighted markups, and in the most recent version we include average markups with many different input weights (expenditure on variable inputs, wage bill, employment,...). Edmond, Midrigan, and Xu (2018) argue that the input weighted markups are the right welfare measure when we have a CES aggregator over different goods and sectors. We completely agree if agents in the economy are indeed endowed with those preferences. Our view is that we should show as many moments (and weights) as possible. We generate a markup observation for each individual firm, and hence the distribution of markups. We therefore show the density, the percentiles, and as many moments and weights as possible. But we do not want to stick to one measure. We believe that there is information also in the average markup weighted by sales shares. First, like GDP, most aggregate measures are sales weighted and not input weighted. Second, if we were to sample a basket of goods such as the basket that constitutes the CPI, or if we wanted to reconstruct a representative bundle of goods, we would use a sales weighted markup. Third, using sales weights there is a link between markups and aggregate profit shares. Moreover, there is information in comparing the input weighted and sales weighted measures. Firms with high markups move up their demand curve because they sell at high prices. As a result, they use fewer inputs yet they generate more sales. This is evident from the reallocation of sales from low to high markup firms. Not surprisingly then will we have more weight on high markup firms when we use sales weights than when we use input weights. The difference between these two measures therefore is further evidence of the reallocation that we document.

4 Concluding remarks

We have tried to clarify some doubts regarding the measurement of markups and market power. Average markups and profit rates are different objects. They inform us about different aspects of the economy. Profit rates inform us about the market power that firms have, while markup tells us in greater detail where it resides and what the role is of technology (returns to scale), fixed costs,... At the core of their difference lies the distinction between variable and fixed costs, and thus variable and fixed factors of production, as well as the degree of substitutability across these factors of production.

Not surprisingly, their magnitudes and evolution are very different. Average markups have gone up by 30-40 points (for the benchmark from 1.21 to 1.61) while profit rates have increased by 7 percentage points from 1 to 8%. Nonetheless, the markup and the profit rate are linked at the firm level, consistent with theory. They are also linked in the aggregate provided we take full account of heterogeneity and the presence of fixed costs and returns to scale.

Using a representative firm framework to analyze aggregate trends in market power is counterfactual and leads to inaccurate conclusions. The same is true for using industry aggregates to analyze the rise of market power. We provide plenty of evidence that heterogeneity matters: median markups and median profit rates are stable, while there has been a stark rise in the higher percentiles of these distributions. In addition, there is robust evidence of reallocation of market share from low towards high markup firms, which is impossible with identical firms.

For many the jury is still out whether there is an increase in market power, and we welcome more discussion, critique and rebuttals. But we do hope the discussion will not be dominated by representative firm reasoning or by the lack of distinction between profit rates and markups.

Appendix A Decomposition of Equation (9) using PF2.

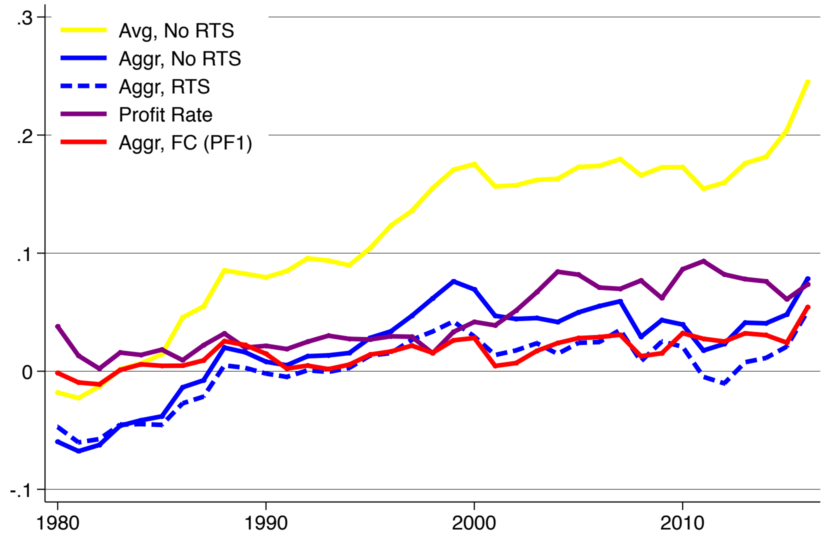
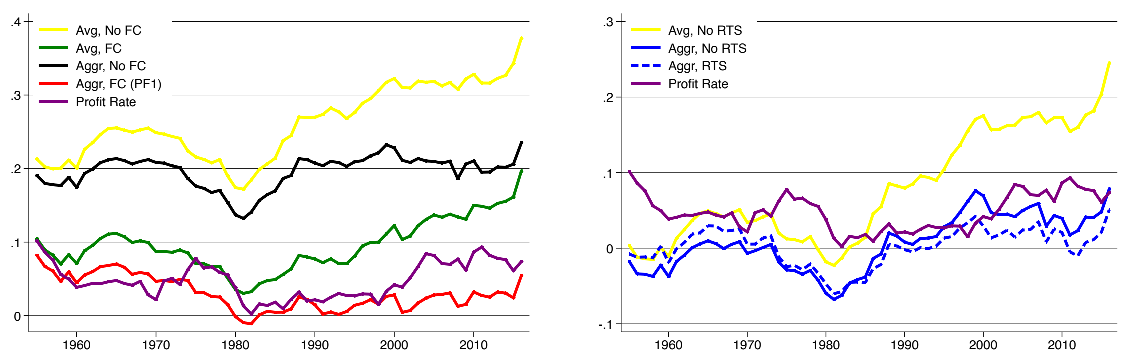


Figure A.1: Decomposition of Equation (9) due to Overhead Costs and Aggregation.

		1980	2016
Use Average	No RTS	-0.02	0.25
Aggregation	No RTS	-0.06	0.08
Aggregation	RTS	-0.05	0.05

Table A.1: Decomposition of the average profit rate from equation (9).



(a) PF1

(b) PF2

Figure A.2: Decomposition of Equation (9) due to Overhead Costs and Aggregation, using both technologies and for 1955-2016.

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