The Rise of Market Power in the UK?

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Abstract

Motivated by the recent work claiming to show an increase in aggregate market power across the developed world, I use rich firm-level financial data, on both private and public companies in the UK, to see whether the same holds for a more representative sample of the economy. For the period 2009 to 2016, I estimate disaggregated sector-specific production functions and estimate firm-level markups over time. I find that aggregate markups are relatively flat over this period, both for private and public firms, and there is little evidence that any of the observed fluctuations are driven by a secular trend of rising overhead expenses. I also find a large heterogeneity across industries, suggesting that focusing on the aggregate trends might be missing some important structural insights.

1 Introduction

Presence of market power in any product market is an important matter for economists as well as antitrust policymakers; while it is also one of the few economic phenomena that are heavily present in public discourse (e.g. Ohio v American Express). On a microeconomic level, lack of competition and the associated market power has implications for consumer welfare and efficiency of production. On a macroeconomic level, it decreases labour demand, investment, as well as discouraging business dynamics and innovation.

Recently, a new literature emerged, starting with De Loecker and Warzynski (2012) (from now on, DLW), and gaining more attention with De Loecker and Eeckhout (2018), which claims that there has been a steady increase in aggregate markups in the US since the 1980s, and that this discovery might help us understand other secular trends such as the decline of the labour share in income, or the increasingly important firm-level fixed effects in labour compensation (e.g. Dorn et al., 2017). Subsequently, they repeated the same exercise for other developed economies (including the UK), and have found very similar patterns. Their estimate of aggregate markups in the UK are reported in Figure 1, and they find that there is a sharp increase in aggregate markups in the UK since 2011.

However, these claims have been heavily debated, both on the grounds of data, as well as methodology. The DLW approach has a great appeal in so far that it allows to estimate markups without having to make

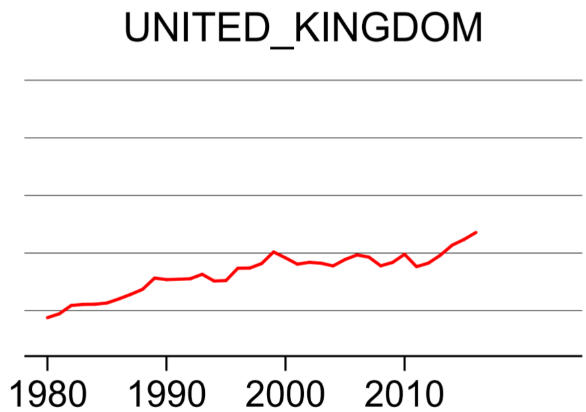

Figure 1: Aggregate markups in the UK, taken from De Loecker and Eeckhout: Global Market Power (2018)

any assumptions on the model of competition or product differentiation. It relies on simple cost minimisation, together with estimating elasticities of variable inputs via production function estimation. The problem with all this is: (i) "aggregate" markups are estimated on the basis of a sample of only public companies (no more that 3% of any economy), (ii) the only data available for production function estimation is financial data, which requires appropriate deflators, ideally on a firm-level, given that the main purpose is to identify pricing behaviour.

Most of the recent debate (e.g. Traina, 2018; Neiman and Karabarbounis, 2018) has focused on the definition of the "variable inputs" that are used in production function estimation. Given the data limitations, De Loecker and Eeckhout (2018) use Cost of Goods Sold as a composite measure of variable inputs. Conversely, Traina (2018) argues that there has been a secular increase in the importance of overhead costs, not directly involved in production, but still important for the overall product - and that this increase is correlated with the increase in markups, suggesting that the omission of these costs from the production function might be generating the sharp rise in markups that De Loecker and Eeckhout find. Still, there is not a unique correct way to calculate markups. These studies use a different set of assumptions and find different results - but there are only a few studies doing so. Since this literature is in its infancy, it requires accumulation of more empirical evidence and methodological variation in order to gain robustness.

Motivated by the stagnation in UK's productivity growth after 2008, as well as its lack of business dynamism and factor reallocation, I try to answer the same question as all of these studies and using a similar methodology; but with two crucial improvements.

Firstly, I use significantly richer firm-level data than any of these studies have used, including both public and private companies, and resulting in around sixty times higher sample. Secondly, to generate real quantities from financial statements, I use disaggregated time series of two/four-digit industrial price indices to deflate the recorded inputs and outputs.

I find that much of the conclusions on markups that De Loecker and Eeckhout, as well as Traina, find for the US does not hold for the bigger UK sample. I find the aggregate markups to be relatively flat in the eight year period spanning from 2009 to 2016. I also find that there is substantial heterogeneity in markup trends across different industries, which suggests that the notion of "aggregate" markups might be misleading when focusing on different economies with different industrial structures. Furthermore, using a sub-sample of only public companies, I find the aggregate markups to be relatively flat; which is opposite from Figure 1.

I also find that Traina's (2018) critique regarding overhead costs of production unplausible for the UK. The share of administrative costs in production, if anything, seems countercyclical to the measured markups, and is positively correlated with them only in few specific industries.

Overall, the UK picture does not seem to be giving a clear answer regarding aggregate market power, since I believe such a concept is misleading to begin with. Still, the estimated heterogeneity in markups across industries and over time might be interesting even if it does not show an unambiguous rise or fall. The fluctuations in these wedges within and across industries could be interacting with other features in the economy, affecting business dynamism and factor reallocation; and this study forms a useful starting point.

2 Model

The standard Industrial Organization approach in estimating markups for a given set of firms usually requires specifying a particular demand system that delivers price-elasticities of demand, which then yields a measure of markups through the first order condition associated with optimal pricing. However, this requires imposing a model of firm competition, as well as modelling demands for each of the products. To estimate markups for all (or at least a significant fraction) of the firms in an economy would thus require specifying models of price competition, together with price and quantity data on a product level; making it unfeasible to do.

However, relatively recently, De Loecker and Warzynski (2012) merged two literatures, one based on production function estimation dating back to Olley and Pakes (1996), Levinsohn and Petrin (2003), Ackerberg et al. (2007), and the other one concerning market power and an old idea of Hall (1988) that markups could be derived from elasticities of production; requiring no assumptions on demand and how firms compete.

The idea is that, if all the firms in an industry are cost minimisers, the Lagrange multiplier of the cost minimisation problem is a direct measure of the marginal cost of production. Thus, in this framework, a firm's markup is defined as the output price (which will depend on market power) over the marginal cost. And, via duality, it is possible to get this ratio by using production function elasticities of variable inputs. Following DeLoecker and Warzynski (2012), assume that a firm i at time t produces output using the following production technology:

$$Q_{it} = Q_{it}(X_{it}^1, ..., X_{it}^N, K_{it}\omega_{it})$$

relying on N variable inputs (labor, intermediate inputs, electricity). Also, firms rely on a capital stock K_{it} (dynamic input). The only restriction imposed on $Q_{it}(\cdot)$ is that it must be continuous and twice differentiable.

Producers in the market are cost minimizers, with the associated Lagrangean:

$$L(X_{it}^1, ..., X_{it}^N, K_{it}, \lambda_{it}) = \sum_{n=1}^{N} P_{it}^n X_{it}^n + r_{it} K_{it} + \lambda_{it}(Q_{it} - Q_{it}(\cdot)).$$

The first-order condition for any variable input, free of any adjustment costs is then:

$$\frac{\partial L_{it}}{\partial X_{it}^n} = P_{it}^n \ - \lambda_{it} \frac{\partial Q_{it}(\cdot)}{\partial X_{it}^n} = 0, \tag{1}$$

where the marginal cost of production for a certain level of output is given by the Lagrange multiplier λ_{it}. Rearranging terms and multiplying both sides by $\frac{X_{it}}{Q_{it}}$ yields:

$$\frac{\partial Q_{it}(\cdot)}{\partial X_{it}^n} \frac{X_{it}^n}{Q_{it}} = \frac{1}{\lambda_{it}} \frac{P_{it}^n X_{it}^n}{Q_{it}}$$

Cost minimization thus implies that optimal input demand is satisfied when firms equalize the output elasticity of any variable input X_{it}^n to $\frac{1}{\lambda_{it}} \frac{P_{it}^n X_{it}^n}{Q_{it}}$. This means that we can simply condition on dynamic inputs of production, such as capital, without having to consider the full dynamic problem of the firm and avoiding additional assumptions.

The firm level markup μ_{it} is defined as price over marginal cost, or:

$$\mu_{it} = \frac{P_{it}}{\lambda_{it}}$$

Using this definition, the previous equation can be rewritten as:

$$\theta_{it}^x = \mu_{it} \frac{P_{it}^x X_{it}}{P_{it} Q_{it}},$$

where θ_{it}^x is the output elasticity of the variable input X_{it}. So, the basis of this approach becomes obtaining this output elasticity.

In principle, there are multiple first order conditions (of each variable input in production) that can yield the expression for the markup. Regardless of which is used, the two key ingredients needed in order to measure the markup are the revenue share of the variable input $\left(\frac{P_{it}^x X_{it}}{P_{it} Q_{it}}\right)$, and the output elasticity of the variable input (θ_{it}^x). It is important to notice that the elasticity of the variable input is by no means restricted in this approach. However, in the the implementation of this procedure, a specific production function needs to be determined, as well as the assumptions of underlying producer behavior that will allow for consistent estimation of this elasticity in the data.

3 Estimation

3.1 Production Function Estimation

Following the standard production function literature (Olley and Pakes, 1996; Ackerberg et al., 2007), I estimate production functions by two-digit industry, which is equivalent to assuming that firms in the same industry have a similar production technology. Since I am covering a time span of only 8 years, unlike e.g. De Loecker and Eeckhout (2018) who utilise almost four decades of data, I do not use time-varying elasticities, and estimate the average production elasticities for each two-digit sector during the entire sample period.

For the benchmark specification, I use a sector-specific Cobb-Douglas production function, with two inputs: a composite variable input bundle and capital as inputs.

For a given firm i, at time t, in industry s, the production function is given by:

$$y_{it} = \theta^v v_{it} + \theta^k k_{it} + \omega_{it} + \epsilon_{it}$$

where lower cases denote logs; $\omega_{it} = ln\Omega_{it}$; y_{it} denotes realized firm's output; and ϵ_{it} is the unanticipated shock to output, or simply classical measurement error in output ($y_{it} = ln(Q_{it}exp(\epsilon_{it}))$.

The main issue with estimating any firm level production function by, for example, simply regressing the observed output on observed inputs is that the contemporaneous productivity shocks which are present in ϵ_{it} will affect adjustable inputs acquisition by the firm, leading to the well-known transmission bias.

However, the standard practice has become to use a two-step control function approach, where it is assumed that there is a part of productivity that the firm anticipates, and a part of it is a contemporaneous shock. If firms choose dynamic inputs (such as capital or labour) a period in advance, their acquisition will be a function of the other inputs and the productivity ω_{it}. If we assume this function is invertible we can proxy for the (unobserved) productivity term ω_{it} by a function of the firm's inputs and a control variable, x_{it}, such that $\omega_{it} = h_{st}(x_{it}, k_{it})$. So, the two step procedure goes as follows:

First step: Obtain estimates of expected output ($\hat{\phi}_{it}$) and an estimate for ϵ_{it} by running

$$y_{it} = \phi_t(v_{it}, k_{it}, x_{it}) + \epsilon_{it}$$

where $\phi_t = \theta^v v_{it} + \theta^k k_{it} + h_{st}(x_{it}, k_{it})$. Productivity ω_{it} is then computed for any value of vector θ, using $\omega_{it}(\theta) = \hat{\phi}_{it} - \omega(v_{it}, k_{it})^T$

Second step: Relying on the law of motion for productivity, which I assume to be an AR(1) process, $\omega_{it} = g_t(\omega_{it-1}) + \xi_{it}$, regress $\omega_{it}(\theta)$ on its lag $\omega_{it-1}(\theta)$, to recover the innovation to productivity: $\xi_{it}(\theta)$.

Here it is assumed that variable input use responds to productivity shocks, but their lagged values do not, and more importantly, that lagged variable input use is correlated with current variable input use, which is guaranteed through the persistence in productivity.

Thus, GMM estimation exploits the fact that capital is assumed to be decided a period ahead so it should not be correlated with the innovation in productivity, while variable input use responds to innovations in productivity (E($x_{it}\xi_{it}$) expected to be nonzero), but lagged values of variable inputs do not.

The associated GMM moments used for estimation are:

$$E\left(\xi_{it}(\theta)\begin{pmatrix} v_{it-1} \\ k_{it} \end{pmatrix}\right) = 0$$

Thus, the GMM estimator solves:

$$\min_\theta\ (Z^T XI)^T (Z^T XI),$$

where Z is a matrix of instruments (including contemporaneous capital, chosen in the prior period, and lagged variable inputs) and XI is the N×1 matrix of innovations to productivity ξ_{it}, calculated as a function of the ω_{it} in the second step. It is also important to notice that in all of the models of production function estimation via a control function, the parameters are exactly identified.

3.2 Calculating markups

Given the model above, after estimating the output elasticity of the variable input, markups are obtained by calculating the ratio between the elasticity and the associated expenditure share of the variable input. However, I do not observe the correct expenditure share for input v_{it} directly since I only observe revenue $\tilde{Q}_{it}$, given by $Q_{it}exp(\epsilon_{it})$, where ϵ_{it} is the aforementioned classical measurement error in output.
So, for a firm i within an industry s, I need to calculate the correct revenue share $\hat{\alpha}$, which is given by:

$$\hat{\alpha}^v_{it} = \frac{P^v_{it} X_{it}}{P_{it}\frac{\tilde{Q}_{it}}{exp(\hat{\epsilon}_{it})}}$$

The markup for a firm i, in time t, in industry s is then given by:

$$\mu_{it} = \frac{\theta^v_s}{\hat{\alpha}^v_{it}}$$

In aggregating these firm-level markups into a two-digit, one-digit, or economy-level measure of trends in markups, following most of the literature, I use sales shares (including both domestic sales and exports) to weight the markups.

Given that the industry-level estimated elasticities are, by assumption, constant over the sample period for all firms in this industry; the intuition behind observing an increase in markups would be that the (corrected) revenue share of the variable inputs is getting smaller and smaller over time, in comparison to the average elasticity.

4 Data

My strategy for estimating markups heavily depends on estimating production functions accurately. Thus, the ideal data for doing so would include physical inputs and outputs over time, with their corresponding prices, for all UK firms. However, the only firm-level panel data recording inputs and outputs that can be compared on a national level come from financial databases.

There are various reasons why estimating production functions from financial data is difficult. For example, firm-level price indices are generally required for generating real variables; while most studies working on similar topics use the aggregate price index to do so. Similarly, studies have shown that most financial statements have an inherent reporting measurement error (Collard-Wexler and De Loecker, 2016), especially in capital. Thus, even if we had the right firm-level price index, the right derived quantities would be mismeasured.

Still, the firm-level financial data used in this study is a substantial improvement with respect to other studies in two ways. I use both private and public firms, in a sample that is around sixty times higher than the Compustat or Worldscope samples of public firms that have been used to estimate markups for the UK (De Loecker and Eeckhout, 2018). This makes me able to somewhat mitigate the extremely small sample issue related to similar studies. Also, in generating real variables from financial variables, I rely on the appropriate industry-level price indices for each variable, which is superior in comparison to the use of the aggregate price index for all variables.

4.1 Firm Data: Amadeus

My UK firm level data is obtained via a large micro dataset of firms' financial accounts provided by Bureau van Dijk (BVD): Amadeus. This database is a commercial product which, for the UK, contains company filings from Companies House, which is a UK government agency acting as the registrar of companies. The database contains information on approximately 2.5 million private and public UK companies yearly, covering the vast majority of the UK corporate universe.

However, BVD provides only live databases, which leads to several limitations. Firstly, the company ownership structure is only accurate at the time of access and not for historical observations, which might lead to double-counting for parent companies which have consolidated accounts in the data.

Still, removing the double-counting, which several institutions have done using vintages of ownership data, the sample is reduced by at most 3%. Also, for the purpose of estimating markups, it is actually desirable to keep all the companies in the sample (even the subsidiaries), which might have a different production function and pricing policies that the parent company itself.

Secondly, companies that die appear to exit the database after some time. Bureau van Dijk, on its official Amadeus product page, says that that "Unlike other kinds of databases, Amadeus is not a historical database and strives for recent information. Financial data for companies within Amadeus is retained for a rolling period of 8 years. When a new year of data is added, the oldest year is dropped, meaning only the most recent data for each company is available." However other researchers have shown that some companies seem to exit the database even sooner (see Appendix for a detailed discussion).

Thirdly, the historical information based on past filed accounts will have significantly more missing data than the most recent filings. To circumvent these issues, some studies (e.g. Foulis et al., 2017) have used archived data sampled at a six monthly frequency to capture information when it was first published.

Still, since I require the firms to have non-missing data on (Net) Fixed Tangible Capital, Cost of Goods Sold and Operating Revenue (Sales), even though the overall number of firms per year goes down by 40% in 2008, in comparison to 2017, the number of firm who have all three reported per year is consistently around 110,000 companies per year. Thus, it appears that the 8-year period that the firms are kept in the sample, together with the 4-12 month reporting lags, make the 2009-2016 sample that I am using a relatively unbiased panel.

The final sample gets substantially reduced due to the fact that companies need to have yearly lagged data for the inputs and output, in order to estimate the AR(1) process for productivity in the second step, so observations with missing lagged data must be dropped. I also drop industries for which output and inputs are poorly measured: Finance (SIC 64), Home sector (SIC 98), Activities of households (SIC 97) and Activities of extra-territorial bodies and organisations (SIC 99). So, all the final results are derived from a sample of approximately 55,000-75,000 companies per year.

4.2 Variables

Due to sample coverage, as well as to be comparable to De Loecker and Eeckhout (2017) and Traina (2018), I use "Cost of Goods Sold" (COGS) as a composite measure of variable inputs to production. This measure is calculated as Cost of Sales less Exceptional Items pre-Gross Profit. It includes variable costs such as materials used in creating the final product, as well as direct labor costs used to produce the good. It excludes indirect expenses, such as distribution costs and administrative expenses.

Recently, the approach of using COGS as a measure of the variable input bundle has been heavily criticised by Traina (2018) and Karabarbounis and Neiman (2018). They argue that the increase in markups is entirely offset by the increase in overhead costs as measured by Selling, General & Administrative Expense (SG&A). However, they bundle variable and fixed factors of production into "Operating Expenses", which I find to be an even less plausible approach, since all estimation hinges on cost minimisation and contemporaneous adjustment of fully variable inputs.

To address this debate, I plot the share of "Other Operatng Expenses" (which is a measure of SG&A in the BvD dataset) in the overall Operating Expenses, together with the associated time series of markups. This is done in order to verify whether a secular increase in the share of overhead costs might be driving the calculated markups.

Year	Sample Size	% Pooled Sample	Public Firms	% Public Firms	Included
2017	9,379	2%	730	8%	No
2016	54,081	10%	2,203	4%	Yes
2015	58,189	11%	2,276	4%	Yes
2014	60,974	11%	2,248	4%	Yes
2013	61,101	11%	2,253	4%	Yes
2012	60,787	11%	2,266	4%	Yes
2011	61,648	11%	2,267	4%	Yes
2010	64,672	12%	2,293	4%	Yes
2009	65,063	12%	2,316	4%	Yes
2008	53,984	10%	1,688	3%	No

Figure 2: Sample statistics

I use "Net Tangible Fixed Assets" as a capital measure, which is calculated directly by BvD. I measure output via "Operating Revenue", which is defined as revenue generated from a company's primary business activities.

4.3 Deflating financial variables

To deflate the financial variables related to the output of firms in a certain industry ("Operating Revenue"), I use the experimental industry level deflators I obtained from ONS. I deflate the capital series with the same industry-level deflators.

However, given that the majority of "Cost of Goods Sold" consists of intermediate inputs, it does not seem reasonable to deflate the inputs with the same prices as the outputs of an industry. For this reason, I use the Input-Output tables from the ONS to generate a price index for the inputs, by weighting the deflators of industries which are intermediate suppliers to a given industry.

4.4 Summary Statistics

I focus my analysis on the 2009-2016 time period. My initial sample started in 2008 due to the fact that in 2007 there was a change in the definition of the SIC codes for UK industries, as well as due to the survivorship bias that arises when downloading BvD data that goes more than 8-10 years back. It ended in 2017 because of the reporting lags, which mean that data that is representative of 2018 has not yet been filed or uploaded to the database. This also resulted in a large sample size drop in 2017, which is why it is not included in the main results either. Sample size and selection is reported in Figure 2.

It is also interesting to examine whether there are any trends in sales, variable inputs and the capital series for the firms in the sample. I plot the lower quartile, median and the lower quartile for each of the three variables over time, separately for all firms, as well as for public firms only. I plot the evolution for public companies separately in order to examine whether there is any prima facie evidence of fundamental differences between the main sample and the sub-sample of public companies. [1] The series are shown in Figure 3.

At a first glance, apart from differences in levels, there does not seem to be much difference in the trends for the entire sample in comparison to public firms only. Still, the variable inputs, as well as revenues, seem to be growing much quicker for the average firm in the entire sample, while the revenues and costs of goods sold are much flatter for the average public firm over time. Thus, in focusing only on public firms, much of the dynamics that seems to be happening among smaller private firms would be lost.

Still, as a side fact, it is interesting to notice the sharp capital growth present for the biggest firms in both samples, while capital is relatively flat for the smaller firms. Even with the scale effects, this suggests that the strong Quantitative Easing initiative in the UK and cheap capital might have had the biggest impact on the investment of companies which were large, with a large collateral and more favourable loan conditions to begin with.

5 Results

[ADD TRAINAS DISC IN ESTIMATION PART]

Given the Cobb-Douglas industry level production function specifications that I am using, I have estimated 164 elasticity parameters in total, and 82 parameters on the composite variable input (COGS) which I am using to calculate markups. Since these are the parameters used for my main results, I present their point estimates (sorted from lowest to highest) with the associated 95% confidence intervals, in Figure 5.

All the variable input elasticities seem to be very tightly estimated (the confidence interval almost overlaps with the point estimates). The only industries whose elasticities seem to be poorly estimated are: Mining (SIC 05), Food Production (SIC 10), Manufacture of tobacco products (SIC 12), Petroleum refining (SIC 19) and Manufacture of ships, railway locomotives and motor vehicles (SIC 30). However, these industries together represent around 1% of the entire pooled sample.

I report Cobb-Douglas markup estimates, aggregated to one-digit industry level, as well as the entire economy over time; together with the share of Administrative Costs in Operating Expenses. I plot them together in order to verify whether Traina's (2018) critique on the rise of Administrative Costs and the potential bias in estimating markups only using costs of goods sold applies to the UK.

I also do the same for a subset of public firms, in order to examine how my estimates compare to De Loecker and Eeckhout's (2018) estimates for the UK, using only public firms from the Worldscope dataset.

[1] The sub-sample of public firms consists of companies which are classified as "Public Company AIM", "Public Company Not Quoted", "Public Company Quoted" or "Public Company Quoted OFEX".

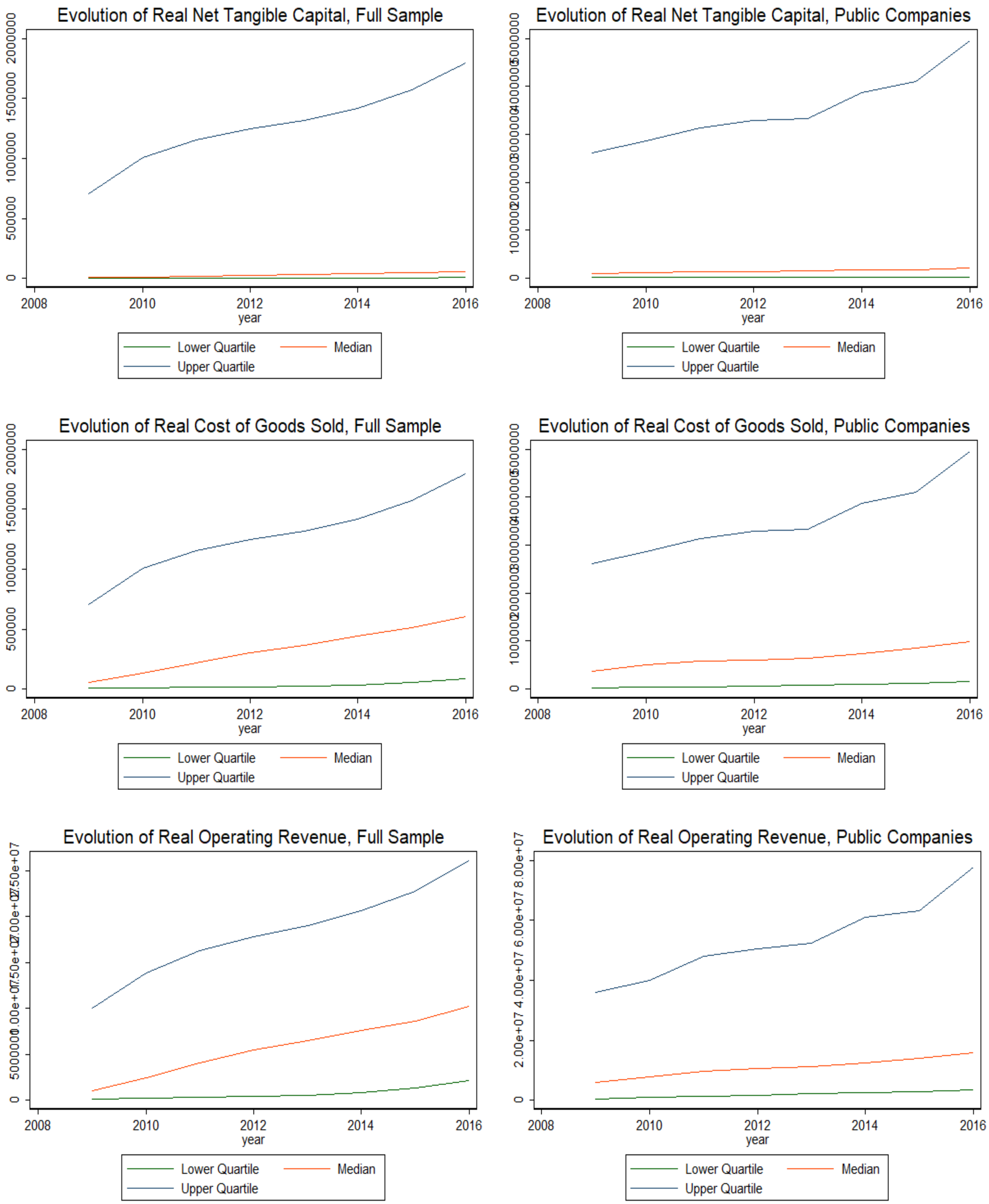

Figure 3: Sample trends in capital, variable inputs and sales over time

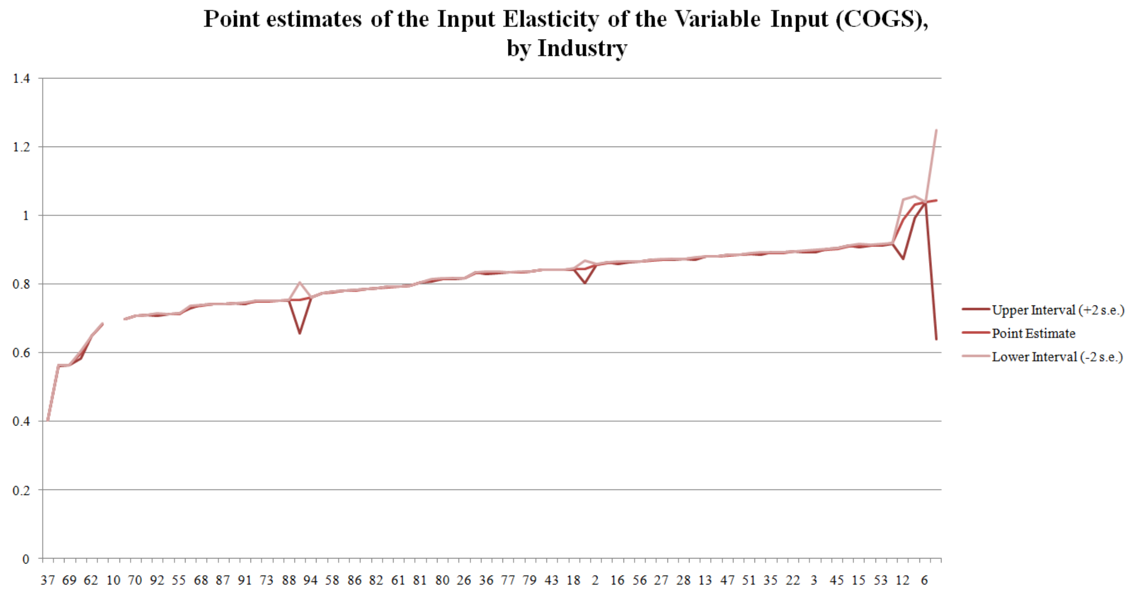

Figure 4: Variable input parameter estimates with the associated confidence intervals

There are a few stylised facts that emerge. Firstly, there does not seem to be an aggregate rise in market power in the UK in the last decade. This is true both for the entire sample, as well as the subset of public firms. My results, thus, contradict similar findings by De Loecker and Eeckhout (Figure XXXXXXXXX), using the exact same methodology. This might be the case because my sample of public firms is still approximately twice the size of the Worldscope one. However, this does point to the main issue regarding all of these studies, and that is whether their conclusions on the rise in markups of public firms in developed countries could be extrapolated to the economy as a whole - and I find that they can not.

An interesting observation, though, is that my economy-level markup estimates using only public firms are similar to the economy-wide estimates using the entire sample, to a great extent. Thus, it would be interesting to examine the sub-sample of public companies which are present in BvD, but not in Worldscope, which would be the ones generating the sample selection disparity.

Secondly, De Loecker and Eeckhout (2018) claim, at least for the US, that the rise in market power that they find is present virtually *within all* industries. I find exactly the opposite: the path of markups over time is very heterogeneous across industries. They experience a sharp rise in Professional, scientific and technical activities; Human health and social work activities; Arts, entertainment and recreation; Other service activities.

They appear to be falling in Mining and Quarrying and Electricity, gas, steam and air coditioning; while they are relatively stagnant in all other industries.

Finally, the point of Traina's (2018) study does not seem to be particularly relevant for the UK over this

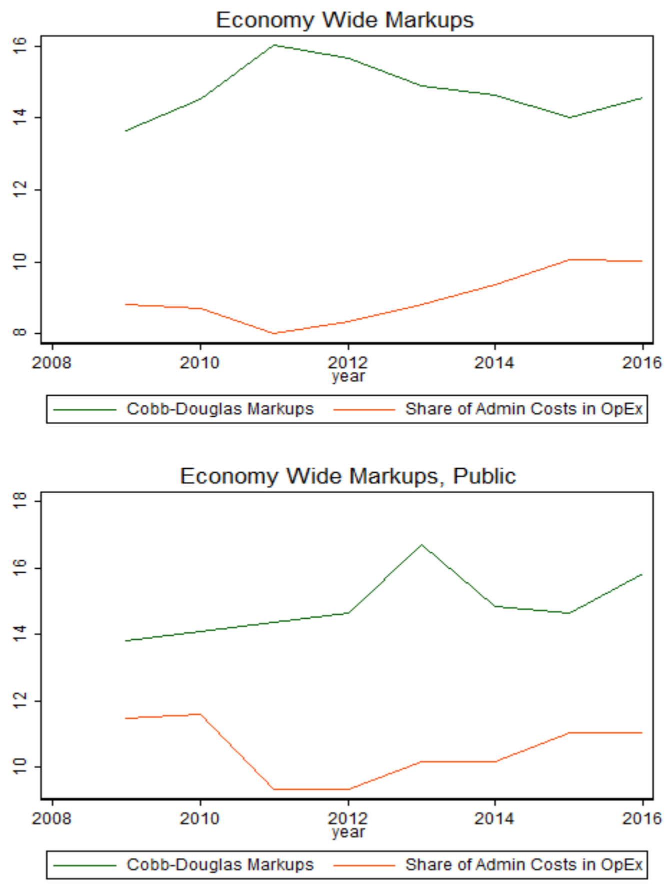

Figure 5: Economy-level markup estimates for the entire sample and public firms, respectively

period. The share of administrative costs in overall operating expenses does seem to be rising, but it is not correlated with markups in most major industries. Also, a stylised fact that is observed both by De Loecker and Eeckhout, as well as Traina, is a strong correlation between size and firm-level markups for the US. However, I find no such relationship, neither for the entire sample, nor for the sub-sample consisting of only public firms.

6 Conclusion

Employing the methodology proposed by De Loecker and Warzynski (2012), I estimate production functions for a large panel of UK firms and find that there is no increase in the aggregate market power in the UK in the period from 2009 to 2016. These results are quite different from the sharp increase in aggregate markups that De Loecker and Eeckhout (2018) find for the UK after 2011. I also find no regularity such as the correlation between size and markup that De Loecker and Eeckhout (2018) report, or the correlation between administrative costs and estimated markups which are emphasized by Traina (2018) and Neiman


Agriculture, Forestry and Fishing
Mining and Quarrying
Manufacturing
Electricity, gas, steam and air conditioning supply
Water, sewerage, waste management and remediation
Construction
Wholesale and retail trade; motor vehicles repair
Transportation and storage
Accommodation and food service activities
Information and communication
Real estate activities
Professional, scientific and technical activities
Administrative and support service activities
Public administration and defence; compulsory social security
Education
Human health and social work activities
Arts, entertainment and recreation
Other service activities
year
Cobb-Douglas Markups
Share of Admin Costs in OpEx

and Karabarbounis (2018).

Thus, I have shown that using richer data and a better approximation for the prices with which the financal data is deflated, might yield to substantially different results; pointing to the fragility of existing results and the need for more empirical evidence and robustness in this line of research.

Still, further robustness could be added to my analysis by using different measures of variable costs in the production function (such as number of employees, labour expenditure or intermediate inputs), and establishing whether the production function estimation and the associated markups turn out similar across the different specifications. The same is true for adding intangible capital or the administrative costs as separate inputs (albeit partially fixed, so markups could not be estimated from their elasticities).

However, the main substance of my results, which rely on richer data, is that focusing on the notion of "aggregate" market power might be misleading, particularly given the heterogeneity in the time-series of markups across different industries in the UK. The focus should not be on the flat aggregate sales-weighted markup series since fluctuations between and across industries in the nominal "wedges" between marginal cost and output prices might propagate through the network and generate substantial implications for the structural macroeconomic dynamics. So, given that that the inter-industry differences feed into one another via intermediate inputs, an interesting extension of these results would be to try to quantify the impact that these markups might have on business dynamism, factor reallocation and productivity, via production networks.

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8 Appendix

8.1 Data

8.1.1 Company Reporting Rules in the United Kingdom

The statutory reporting requirements for companies registered in the United Kingdom are mainly governed by the Companies Act 2006 and prior to that the Companies Act 1985. The last provisions of the Company's Act 2006 came into force in 1st October 2009. This means that for the most of my sample period (2008-2017) firms in the United Kingdom operated with the same reporting standard. The Act covers private and public limited companies. Other types of companies (e.g. Partnerships or LLPs) are covered by separate legislation but have their own reporting standards and still must file their accounts.

Companies House is the Registrar of companies in the United Kingdom. The agency has the responsibility for examining and storing all the statutory information that companies in the United Kingdom are required to supply. Companies House also has the responsibility to make the filed information public; however, there are exceptions to what a company have to make publicly available.

At the end of the a company's financial year a company must prepare a set of statutory annual accounts that they file with Companies House. These include a version of the firm's balance sheet and profit and loss account. All limited companies are required to report in some way or another to Companies House. However, reporting requirements, particularly over the annual accounts, vary by firm size. So in my case, the sample will be biased towards larger firms which are required to report detailed items in the profit and loss account (e.g. costs of variable inputs).

Companies have 21 months from incorporation to file their first set of accounts with Companies House. Subsequent annual accounts must be filed within 9 months of the company's financial year end for private companies and 6 months of the company's financial year end for public companies. Companies can amend the accounts retrospectively to fix errors and present data revisions. Companies can also amend the end of their accounting year (but not retroactively), which can lead to irregular accounting windows of different lengths than a year. However, companies must file accounts every 18 months.

8.1.2 BvD's Collection and Coverage of Firms in the United Kingdom

Companies House is the original source of my data but the direct source is Bureau van Dijk (BvD), who aggregate the data and provide it through the Wharton Research Data Service (WRDS) interface. For the United Kingdom, BvD provides firm-level data through a UK-specific database called FAME (Financial Analysis Made Easy), as well as through the more commonly used Amadeus and Orbis products which cover firms at the European and Global level respectively (the UK firms form a subset in both data sets). I am using the Amadeus database via WRDS.

However, BvD does not source its data from Companies House directly. In between Companies House and BvD is another data provider, Jordans; which then serves as the direct source for BvD. In the FAME user guide BvD describes the logistics of the data collection procedure from Companies House, to Jordans, and then to BvD; and this time frame would imply that most live companies in the BvD database would have their latest accounts filed within the past year (9 months after the firm's financial year plus one-two month's processing time) but many institutions have found (e.g. Bank of England) that lags of two years are not uncommon. Given that lags can occur at four different stages (the filing stage and the three processing stages by Companies House, Jordans and BvD), it is unclear what might be causing this.

Taking a conservative approach, I have assumed all firms to have a 6-month lag between the accounts filing date in the BvD data and the time period for which the accounts are relevant. However, some companies change their filing date over the time period which I am looking at (2008-2017), which, when implementing the time lags procedure, might generate two observations for a firm in a given year. In generating a panel, for such instances I have kept the latest observation for a given year.

There is conflicting information regarding how long inactive companies remain in the Amadeus database. Via informal communication, BvD claimed that Jordans (their data provider) keeps inactive companies in the database for five years, so those firms would be lost from the source material. However, BvD then (on a quarterly cycle) re-uploads the missing companies from their own archives ensuring that no data is lost from any of their products. However, this claim may not be accurate. Foulis et al(2017), using Blu-Ray vintages of the data, together with the live database that I am using, have found that firms did indeed exit the database. For instance, in the FAME database, almost 50% of firms in the database in January 2005 were not present 10 years later.

8.2 Industry-level Markups: Public Companies