Converging to Mediocrity: Trends in Firm-Level Markups in the United Kingdom 2008-2019

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Abstract

UK manufacturing firms have experienced sharp declines in productivity since 2008, whether measured by real revenue per worker or estimated total factor productivity. Less is known about trends in firms' markups, which is important for understanding productivity dynamics. The estimation of markups is challenging without direct access to price and cost data, but they can be inferred using microdata on firms' revenues and input use. In this paper we use two approaches to infer the evolution of aggregate markups for UK manufacturing firms. Both use estimates of the elasticity of substitution within industry subsectors. Our principal approach involves assumptions about the structure of competition between firms at various levels of industry aggregation, while the second uses the influential production approach to infer the markup based on variable input cost shares. Both approaches show declines in estimated UK manufacturing markups since the financial crisis, estimating a decrease in industry-level gross markups of approximately two to five percentage points between 2008 and 2019. There are significant contributions from within-firm declines rather than reallocation. As markup declines are associated with an adverse shift in the distribution of firm-level manufacturing productivity, our results indicate that structural dynamics in manufacturing industry likely play a large part in the UK's productivity puzzle.

1. Introduction

The rapid advance of digital technologies has been associated with a number of adverse aggregate economic trends, including a slowdown in the rate of productivity growth, reduced economic dynamism, rising wage inequality, a fall the labour share and an increase in the average markups associated with rising market power (Elsby et al., 2013; Autor et al., 2020; De Loecker et al., 2020). These trends have been linked, at least in part, to the increasing returns to scale associated with the new technologies, where the sources of the increasing returns have potentially both supply- and demand-side origins. On the supply side, one source is the higher fixed costs associated with intangible investments (see, e.g., Tambe et al 2020, Haskel and Westlake, 2018). On the demand side, the network effects associated with platform technologies favour the emergence of winner-take-all markets. One implication of these changes is the rise in "superstar firms" that have outsized prominence in their industries (Autor et al., 2020; De Loecker et al., 2020; Eeckhout, 2022). While technology-enabled superstar firms have brought some consumer benefits, their market dominance has led to greater heterogeneity in firm-level productivity and raised average markups.

While the US has been the main focus of this research, there is some evidence that other countries have experienced similar trends. De Loecker and Eeckhout (2018) find that globally the average (gross) firm-level markup has risen from 1.1 to 1.6, with the largest increases found in Europe and North America. Diez et al. (2021) report smaller increases in average markups but find more pronounced increases in services and for firms in advanced economies. Karabarbouis and Neiman (2014) find evidence of a declining global labour share in the 1980s, with the fall occurring in a large majority of countries and industries.

There are relatively few studies looking at the UK specifically. Some conclude the UK experience has been similar to the US. De Loecker and Van Reenen (2022) report largely parallel trends to those in the US for key aggregate measures such as the average markup and the labour share. Using the data of UK listed companies, Aquilante et al. (2019) measure the variable inputs using intermediate consumption data and find large increases in manufacturing mark-ups. However, the CMA (2024) finds the labour share in the UK had been stable, while Karabarbouis and Neiman (2014) also highlight the difference between the UK and other advanced economies in labour share trend. ONS

(2022) also finds that mark-ups in UK manufacturing between 1997 and 2019 have been relatively flat rather than increasing.

The UK is also distinctive in the extent to which its labour productivity growth has fallen since the financial crisis, with more than half the fall attributed to a decline in the growth of total factor productivity (Van Reenen and Yang, 2023; Goodridge and Haskel, 2023). Based on a sectoral analysis, Coyle and Mei (2022) find that this decline in productivity growth is mainly attributable to particular industries, notably manufacturing and ICT. Relatedly, Goodridge and Haskel (2023) find the largest slowdowns have occurred in the most intangible- and digital-intensive industries.

While the aggregate trends may be similar across many advanced economies, Coyle et al. (2024) show that patterns can be quite different for individual industries. In UK manufacturing, they find evidence of a both a falling trend for within-firm TFP and falling dispersion in TFP across firms. Therefore, in contrast to patterns seen elsewhere, UK manufacturing is characterised by what might be called a "convergence to mediocrity". This is captured in Figure 1 by the substantial number of firms experiencing TFP contraction and a negative relationship between the lagged market share and TFP growth. Figure 2 further highlights the shift in the TFP distribution, with 2019 exhibiting a leftward shift compared to that of 2008.

Our contribution in this paper is to extend the Coyle et al. (2024) analysis of the performance of the UK manufacturing sector by looking in particular at the trends in both the average markup and its dispersion among firms. Decreasing firm heterogeneity would be expected to lead to both a fall in the average level and its dispersion. These patterns that would, on the face of it, be at odds with the rising importance of superstar firms elsewhere.

Although the estimation of markups is challenging without direct access to price and cost data, they can be inferred using microdata on firms' revenues and input use. In this paper we adopt two alternative methods, involving different assumptions, for identifying and then estimating markups for UK manufacturing firms using micro data from the Annual Business Survey since the financial crisis 2008-2019.

The production approach has dominated the recent literature on markup estimation. This approach, which has origins in seminal contributions of Hall (1988) and De Loecker and Warzynski (2012), has the appeal that it does not require structural assumptions about demand or the form of product market competition. Instead, it relies only on cost minimisation by firms operating in competitive input markets. As an implication of the first-order-condition for a flexible input in the cost-minimisation problem and the definition of the (gross) markup, the markup is obtained as the ratio of the output elasticity of that input to its share of total firm revenue, and is consequently sometimes referred to as the ratio estimator.

Despite its wide application, the production approach has been the subject of recent criticisms. Raval (2023) and CMA (2024) demonstrate the high sensitivity of inferred markups to the assumption about the flexible input – labour or materials – used in the calculation. Foster et al. (2022) show that the De Loecker et al. (2000) finding of a sharply rising average markup in the US largely disappears when more fine-grained (6-digit) data is used. At a more fundamental level, Bond et al. (2022) argue that the required output elasticities cannot be identified using deflated revenue data rather than separate data on prices and quantities; they show that using the revenue elasticity in place of the output elasticity implies a markup that is identically equal to 1. More positively, De Ridder et al. (2024) compare the inferred markups using revenue data and data on prices and quantities in both simulated and actual data and find a high correlation between the two at the firm level. However, they also find that while the markup estimations may be informative about the direction of the trend and dispersion of average markups, the use of revenue data leads to biased estimates of their level.

Our preferred, baseline method therefore relies on structural assumptions for demand (nested Cobb-Douglas/CES with time- and firm-varying product quality), technology (Cobb-Douglas with time- and firm-varying Hicks-neutral technology) and market structure (quantity competition among differentiated product firms). In principle, this approach allows us to infer firm-level markups from the estimated revenue function. Importantly, the method makes use of an estimate of the demand-side elasticity of substitution in an industry to adjust for price effects (Klette and Griliches, 1996). Our specification of quantity competition draws on Atkenson and Burstein (2008). We show that the markup is inferred under quantity competition as a function of the demand-side elasticity of substitution and the firm's revenue share in an industry. With monopolistic competition, the elasticity of substitution is equal to a firm's price elasticity of demand under our functional form assumptions. However, the two are not equal under the assumption of quantity competition; in this case we show that a firm's markup is a convex function of its revenue share. Moreover, given this convex relationship, an increase in the dispersion of market shares is associated with an increase in the average industry markup.

As our estimated revenue function also allows us to infer the output elasticities of inputs, our second method applies a version of the production approach using these elasticities. This approach still makes use of our structural assumptions for demand and technology but makes no assumption about the form of product-market competition. We choose materials as the best candidate for the flexible input in our data. However, given the limitations of the production approach noted above, we do not rely on it in our calculation of the average markups, but instead use it as a check on the directional trends and dispersion measures that are produced using our baseline quantity-competition method.

Overall, we find that UK manufacturing indeed differs from other advanced economies and in particular contrasts with the US. Rather than a superstar firm evolution, firms in the UK are indeed "converging to mediocrity", with a downward shift in the distribution of mark-ups and a lower average level and dispersion. On the average level of markups using demand approach, we find that it initially decreased from roughly 1.2 in 2008 to 1.17 in 2009, but then increased to about 1.27 in 2011. Since 2013, there has been a sharp decrease until 2019, when the markups were below 1.15 compared with above 1.2 in 2008. On the growth index, we find that average revenue-weighted markups index declined by about 5%, dropping from above 1.05 in 2010 to below 0.95 in 2019. The result shows that the declining trend is driven mainly by the within term, falling by about 6% from 2011 to 2016. On the results of markups using production approach, we then find that the trends are quite different with our demand approach, but the overall declining trend remains the same. The results confirm that the overall markup decreases but with a less steeply declining trend compared to our demand approach; throughout the period 2008-2019, the production approach markups decrease by 2%.

The rest of this paper proceeds as follows. Section 2 sets out the model framework and estimation methodology. Data are discussed in section 3 and estimates are presented in section 4. Section 5 discusses the implications of our findings and concludes.

2. Markup Estimation Framework

2.1 Basic Structure of the Economy

2.1.1 Consumer preferences

Consumers are assumed to have a Cobb-Douglas utility function over CES indexes of manufactured goods, Z_t, and an index of services, X_t:

$$U_t = Z_t^{\alpha} X_t^{1-\alpha} \, . \tag{1}$$

As the nested utility function is homothetic, we can sum (1) over consumers to get the aggregate output index, Y_t, and can define the aggregate price index, P_t, such that $P_{Zt}Z_t + P_{Xt}X_t = P_tY_t$. The prices of a unit of the Z_t index and a unit of the X_t index are P_{zt} and P_{Xt} respectively. Maximising their utility, the representative consumer allocates their nominal income over the two aggregates to yield expenditure shares:

$$P_{Zt}Z_t = \alpha \, P_tY_t \tag{2}$$

$$P_{Xt}X_t = (1-\alpha) \, P_tY_t \, . \tag{3}$$

where P_tY_t is nominal income.

Aggregate manufacturing output in a given industry is a (homothetic) CES function of the quality-adjusted goods produced by the N firms in the industry:

$$Z_t = \left[\sum_{i=1}^{N} (\Lambda_{it} Q_{it})^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}}, \tag{4}$$

where Λ_{it} is a measure of the quality of the good produced by firm i at time t, Q_{it} is the volume output produced by firm i at t and η is the elasticity of substitution between the N goods in the index. (Identical results apply to services.) We thus incorporate both a representative consumer with a preference for variety and vertical differentiation based on quality between products that enter into the industry output index. We denote quality-adjusted output as $Q_{it}^{*} = \Lambda_{it} Q_{it}$.[1] We assume that $\eta > 1$ and that each firm produces a single product variety.

2.1.2 Manufacturing firms' production functions

We next derive the demand curve facing an individual firm in the manufacturing sector producing a good with the quality level Λ_{it}. Given the allocation of income to manufacturing goods, we can use standard results in the literature to derive the demand function facing the firm Λ_{it} as:

$$Q_{it} = \Lambda_{it}^{\eta-1} \left(\frac{P_{it}}{P_{Zt}}\right)^{-\eta} Z_t$$
$$= \Lambda_{it}^{\eta-1} \left(\frac{P_{it}}{P_{Zt}}\right)^{-\eta} \frac{\alpha\, P_t Y_t}{P_{Zt}}, \qquad (5)$$

where the price index for the industry, P_{Zt}, is given by:

$$P_{Zt} = \left[\sum_{i=1}^{N} \left(\frac{P_{it}}{\Lambda_{it}}\right)^{\eta-1}\right]^{\frac{1}{\eta-1}}. \qquad (6)$$

From (6), we can see that quality improvements are reflected in a lower industry price index. Moreover, the effect of a change in quality on the cost of achieving a particular level of Z_t is equivalent to a price change of equal proportion but opposite in sign.[2]

Turning to the production function for a firm i in the manufacturing sector in year t, we assume each firm has the Cobb-Douglas production function technology:

[1] Quality change thus enters the utility function in a "better is more" form (for a related analysis in the context of combining different vintages of capital in a capital aggregate, see Fisher (1965) and Hulten, (1992).

[2] Fisher and Shell (1972) consider the case where a quality improvement for a given good affects the utility of other goods – for example, improvements in the quality of refrigerators also affects the utility from consuming ice cream. They show that where the 'qualities' of other goods are affected, the correct accounting for the effect of the initial quality change on the cost of living (here the cost of achieving a given Z_t) will require adjustments in the equivalent prices of the other goods affected (here adjustments in the relevant "quality" levels of the other goods affected). This will also apply where the quality change for one good causes a reduction in the utility from other goods. For example, when the improvement in the quality of one brand of ice cream reduces the utility from the unimproved brands that are also being consumed. A change in a particular good's Λ_{it} captures relative as well as absolute changes in quality.

$$Q_{it} = \Omega_{it} L_{it}^{\beta_l} K_{it}^{\beta_K} M_{it}^{\beta_m} \tag{7}$$

where Ω_{it} is a (firm-specific) measure of Hicks-neutral technical change, L_{it} is labour, K_{it} is fixed capital and M_{it} is materials.

2.1.3 Firm revenue functions

To derive the firm revenue function, we first write the demand function (5) in inverse form as:

$$\frac{P_{it}}{P_{Zt}} = \Lambda_{it}^{\frac{\eta-1}{\eta}} Q_{it}^{-\frac{1}{\eta}} \left(\frac{\alpha\, P_t Y_t}{P_{Zt}}\right)^{\frac{1}{\eta}} \tag{8}$$

where the quality indicator, Λ_{it}, is a shift factor for the inverse demand function. As noted above, such shifts in quality can reflect relative as well as absolute changes in quality that correspond to changes in the representative consumer's marginal willingness to pay.

Using (2), (7) and (8), total deflated firm revenue is:

$$\frac{R_{it}}{P_{Zt}} = \frac{P_{it}Q_{it}}{P_{Zt}} = (\Lambda_{it}\Omega_{it})^{\frac{\eta-1}{\eta}} \left(\frac{R_{Zt}}{P_{Zt}}\right)^{\frac{1}{\eta}} L_{it}^{\frac{\eta-1}{\eta}\beta_l} K_{it}^{\frac{\eta-1}{\eta}\beta_K} M_{it}^{\frac{\eta-1}{\eta}\beta_m} \tag{9}$$

where industry revenue is R_{Zt}=$P_{Zt}Z_t = \alpha\, P_t Y_t$.

From (9), total revenue varies with the increased use of factors of production for two reasons. First, an increase in the use of a factor of production (say labour) leads to an increase in physical output; and second, the firm must lower its price to sell this increased level of output given that it faces a downward sloping demand curve. The coefficient on each input is the revenue elasticity of the input, $(\eta - 1/\eta)\beta_f$ for $f \in (l,k,m)$, where the revenue elasticity will be lower than the output elasticity given our assumption that $\eta > 1$.

Taking natural logs of (9) and rearranging we obtain:

$$r_{it} - p_{Zt} = \frac{1}{\eta}(r_{Zt} - p_{Zt}) + \frac{(\eta-1)\beta_l}{\eta} l_{it} + \frac{(\eta-1)\beta_k}{\eta} k_{it} + \frac{(\eta-1)\beta_m}{\eta} m_{it} + \frac{(\eta-1)}{\eta}(\lambda_{it} + \omega_{it}) \tag{10}$$

where lower case letters represent the natural log of a variable. A convenient feature of (10) is that identification of η is possible from the estimated coefficient on the deflated-industry-revenue variable in the estimated firm revenue function (Griliches and Klette, 1996) through each SIC4 sector.[3] Using this estimate of the elasticity of substitution, the output elasticities β_l, β_k and β_m can then be obtained from the estimated coefficients on l_{it}, k_{it} and m_{it} respectively.

2.2 Inferring Firm-Level Markups

2.2.1 Heterogeneous markups under quantity competition

Up to this point, we have not made any assumption about how firms set prices. If manufacturing firms were operating under monopolistic competition the markup would be homogenous across firms in an industry and constant over time under our assumptions. This constant markup is given by the familiar formula:

$$\mu_{it}^{M} = \frac{\eta}{\eta - 1} \tag{11}$$

where η is both the price elasticity of demand and the elasticity of substitution between goods in the manufacturing index. To allow for heterogeneous markups, we instead assume that the differentiated product firms engage in (Cournot-style) quantity competition. In particular, we assume that firms consider the effect of their output choices on the industry's output and thus on the industry price level. To solve for the equilibrium, we adapt the method in Atkeson and Burstein (2008) for our assumed functional forms (i.e., CES industry aggregates nested within a Cobb-Douglas utility function) to obtain the relevant firm- and time-varying markups.

We assume that an industry is in equilibrium with a given set of firm outputs (and associated firm prices and revenue shares). Under quantity competition, each firm makes its output choice taking the output choices of the other firms in the industry as given. In contrast to monopolistic competition, however, each firm is assumed to be sufficiently large that it takes into account the effect of its output choice on aggregate industry output.

[3] See Table A1 SIC4 classification in the Appendix.

This effect on industry output in turn affects the firm's perceived price elasticity of demand and consequently their optimal markup.

Although each firm is assumed to be sufficiently *large* in relation to the respective industry, we assume that each firm is sufficiently *small* in comparison to the total economy that they do not take into account any effect their choices have on aggregate total output (Y_t) and thus the aggregate total economy price index (P_t). Using the fact that $P_{Zt}Z_t = \alpha P_t Y_t$, we first substitute the industry price index out of the inverse demand curve (8):

$$\frac{P_{it}}{P_t} = \Lambda_{it}^{\frac{\eta-1}{\eta}} Q_{it}^{-\frac{1}{\eta}} Z_t^{\frac{1}{\eta}} \frac{\alpha Y_t}{Z_t} \tag{12}$$

Now using (4), we can write the elasticity of the industry output index with respect to the firm's output choice as:

$$\frac{dZ_t}{dQ_{it}} \frac{Q_{it}}{Z_t} = \left[\sum_{i=1}^{N} (\Lambda_{it} Q_{it})^{\frac{\eta-1}{\eta}}\right]^{-1} (\Lambda_{it} Q_{it})^{\frac{\eta-1}{\eta}} \tag{13}$$

Separately, multiplying both sides of (8) by Q_{it}/Z_{it}, we obtain the revenue share of firm i, s_{it}, in industry revenue as:

$$s_{it} = \frac{P_{it} Q_{it}}{P_{Zt} Z_t} = \left[\sum_{i=1}^{N} (\Lambda_{it} Q_{it})^{\frac{\eta-1}{\eta}}\right]^{-1} (\Lambda_{it} Q_{it})^{\frac{\eta-1}{\eta}} \tag{14}$$

Noting that the right-hand-sides of (13) and (14) are identical, we therefore have:

$$s_{it} = \frac{dZ_t}{dQ_{it}} \frac{Q_{it}}{Z_t} \tag{15}$$

i.e., the elasticity of the manufacturing index with to firm $i's$ output choice is equal to that firm's share in industry revenue. Taking natural logs of (12) and rearranging we obtain:

$$p_{it} = p_t + \left(\frac{\eta-1}{\eta}\right) \lambda_{it} - \frac{1}{\eta} q_{it} + \frac{1}{\eta} z_t + ln\alpha + y_t - z_t \tag{16}$$

The partial derivative of (16) with respect to with respect to q_{it} (taking p_t, y_t, λ_t and α as given), gives an expression for the inverse price-elasticity of demand under quantity competition:

$$\begin{aligned} \frac{dp_{it}}{dq_{it}} &= -\frac{1}{\eta}\left(1-\frac{dz_t}{dq_{it}}\right)-\frac{dz_t}{dq_{it}} \\ &= -\frac{1}{\eta}(1-s_{it})-s_{it} \end{aligned} \tag{17}$$

where the second step uses the equality between the market share and the elasticity of the manufacturing output index with respect to firm output given in (15) above. Inverting (17) and multiplying through by minus 1 gives an expression for the absolute price elasticity of demand of a firm:

$$\epsilon_{it} = -\frac{dq_{it}}{dp_{it}} = \frac{1}{\frac{1}{\eta}(1-s_{it})+s_{it}} \tag{18}$$

Finally, using the standard formula for the (gross) markup, we obtain the markup for firm i at time t under quantity competition as:

$$\mu_{it}^{QC} = \frac{\epsilon_{it}}{\epsilon_{it}-1} = \left(\frac{1}{1-s_{it}}\right)\left(\frac{\eta}{\eta-1}\right) \tag{19}$$

A firm's markup under quantity competition is therefore a multiple of the markup under monopolistic competition, with the size of the "multiplier" depending on the firm's share in total industry revenue.[4] A firm having a higher revenue share both in the cross section of industries and over time is thus associated with a higher firm-level markup. Intuitively, firms with a higher market share contribute a larger positive effect of an increase in their output on the manufacturing output index and therefore a larger negative effect on the industry price index, resulting in more price elastic demand and consequently a higher optimal markup. We note that improvements in product quality (i.e., a higher Λ_{it}) or improvements in technical efficiency (i.e., a higher Ω_{it}) will, all else equal, increase a

[4] A similar qualitative result would be obtained if we instead assume that firms compete as differentiated-product Bertrand competitors.

firm's $TFPQ^*$ and consequently its revenue share, and thus will be associated with an increase in its markup.

For a given industry-level elasticity of substitution, there is a convex relationship between a firm's market share and its optimal markup. The non-linearity implies that increasing concentration is associated with a rising revenue-share-weighted industry markup, which follows as a standard application of Jensen's inequality. We demonstrate this with a simple example of a two-firm industry in Figure 2. When the firms have equal market share of 0.5 the revenue-weighted markup is μ_t^A in Figure 3. However, as concentration increases – here captured by assuming heterogeneous revenue shares of 0.2 and 0.8 – the revenue-share-weighted markup rises to $\mu_t^B > \mu_t^A$.

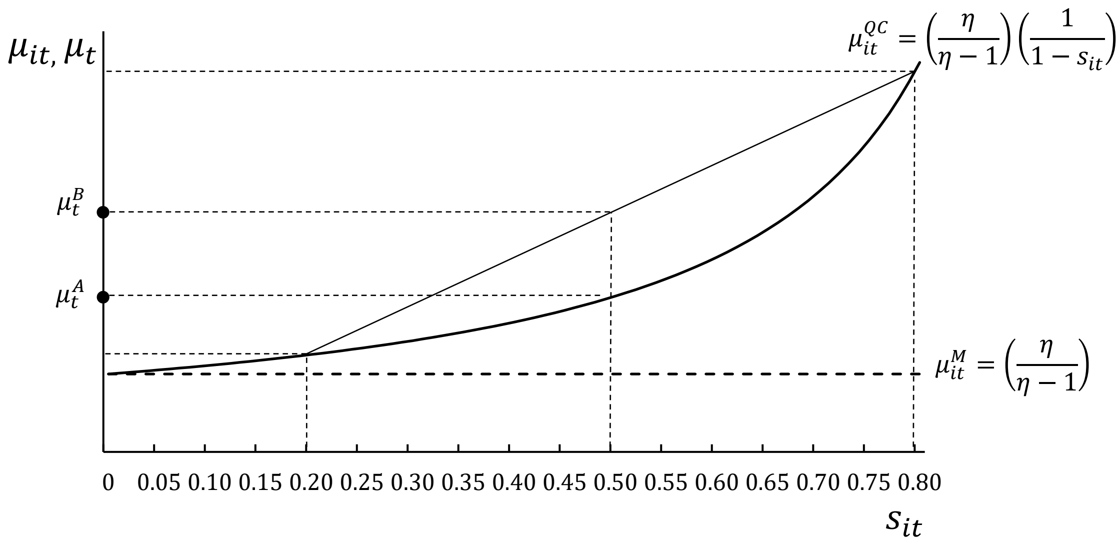

Figure 2. Relationship between Revenue Share and Markup at Firm and Industry Levels

Finally, for the task of inferring markups, the fact that under our assumed quantity competition the markups depend only on the elasticity of substitution between products in an industry and the revenue shares means we can infer the distribution of markups using our estimate of the relevant industry elasticity of substitution and the revenue shares from the data. We discuss our approach to consistently estimating the parameters of the revenue function in Section 2.4 below.

2.2.2 The alternative production approach

A limitation of the previous approach to inferring markups is that it relies on a specific model of quantity competition in an industry. As an alternative to making strong structural assumptions to recover markups, we also use a variant of the production approach involving alternative assumptions to enable identification of markups (Hall, 1986; De Loecker, 2011; De Loecker and Warzynski, 2012). This approach assumes only cost minimisation at the firm level and requires information on the share of a flexible input in the total revenue of the firm and the output elasticity of the flexible input that we can obtain from our estimated revenue function. We select material input as the flexible input in our application; as noted in Section 1, the results in the production approach may be sensitive to the choice.

For the case of a general production function, $Q_{it} = F(L_{it}, K_{it}, M_{it})$, the Lagrangian for the cost-minimisation problem is:

$$\mathcal{L}_{it} = P_{L,t}L_{it} + P_{K,t}K_{it} + P_{M,t}M_{it} + \chi_{it}\,(\overline{Q_{it}} - F(L_{it}, K_{it}, M_{it})), \tag{20}$$

where $P_{L,t}, P_{K,t}$ and $P_{M,t}$ are the prices of labour, capital and materials respectively in period t and χ_{it} is the Lagrangian multiplier, which is also equal to marginal cost. The first-order-condition (FOC) with respect to the variable materials input is:

$$\begin{gathered} \frac{\partial \mathcal{L}_{it}}{\partial M_{it}} = P_{M,t} - \chi_{it}\,\frac{\partial Q_{it}}{\partial M_{it}} = 0 \\ \Rightarrow \frac{\partial Q_{it}}{\partial M_{it}} = \frac{P_{M,t}}{\chi_{it}}. \end{gathered} \tag{21}$$

Now multiplying both sides of the last equation by Q_{it}/M_{it} and using the definition of the (gross) markup as $\mu_{it}^{PA} = P_{it}/\chi_{it}$, we obtain:

$$\mu_{it}^{PA} = \frac{\beta_{M,it}}{s_{M,it}}, \tag{22}$$

where $\beta_{M,it}$ is the elasticity of output with respect to the flexible input and $s_{M,it}$ is the share of material input cost in total firm revenue. In our particular case of a Cobb-Douglas production function with constant output elasticities across time and firms, the FOC imply:

$$
\begin{aligned}
\beta_M \frac{Q_{it}}{M_{it}} &= \frac{\mu_{it} P_{M,t}}{P_{it}} \\
\Rightarrow \quad \mu_{it}^{PA} &= \frac{\beta_M}{s_{M,it}}.
\end{aligned}
\tag{23}
$$

Thus the markup can be inferred from the implied output elasticity of the flexible materials input from our revenue equation and the share of the material input relative to total firm revenues.

As stated, this inferred markup has no relationship to the firm's share in total industry revenue and thus has no direct implication for the effects of increasing industry concentration on the revenue-shared weighted industry average industry markup. However, such a relationship would be implied if there is a relationship between the firm's material input share in total firm revenue, $s_{M,it}$, and the firm's share in total industry revenue, s_{it}. Such a relationship could exist, for example, if more productive firms with larger shares of industry revenue invest more in intangible assets (either capital or labour) and thus have a lower share of material input in total firm revenue. Suppose, for illustration, the relationship is given by the simple linear form: $s_{M,it} = a - bs_{it}$ (where we assume $0 < a - bs_{it} \leq 1$). The markup would then simply be:

$$
\mu_{it}^{PA} = \frac{\beta_M}{a - bs_{it}}, \tag{24}
$$

which has a similar form to the firm-level markup under quantity competition, (19), with β_M replacing $\eta/(\eta - 1)$ in the numerator of the markup equation and the markup also having a convex relationship to the revenue share of the type shown in Figure 1. Increasing concentration would then also be associated with increases in the revenue-weighted average industry markup as discussed in the previous subsection.

We estimate industry markups using both the baseline quantity competition method, μ_t^{QC}, and the production approach, μ_t^{PA}, in our empirical application. We also underline that both methods rely on our estimation of the revenue equation (10), although the two methods make use of different estimated parameters of that equation.

2.3 Evolution of the Aggregate Manufacturing Markup

Following the approach of De Loecker et al. (2020), we decompose the evolution of aggregate manufacturing markup into the sum of a measure of the evolution of within-firm markups, a measure of reallocation effects, and a measure of entry and exit effects. Denoting the aggregate markup as μ_t, we first express it as a revenue-share-weighted average of the corresponding firm-level measures:

$$\mu_t = \sum_i \mu_{it} s_{it} \tag{25}$$

Using the DeLoecker et al. (2020) decomposition, we can write the change in the aggregate markup as a sum of five components:

$$\Delta\mu_t = \sum_i \Delta\mu_{it} s_{it-1} + \sum_i \hat{\mu}_{it-1} \Delta s_{it} + \sum_i \Delta\mu_{it} \Delta s_{it} + \sum_{i\in Entry} \hat{\mu}_{it} s_{it} + \sum_{i\in Exit} \hat{\mu}_{it-1} s_{it-1} \tag{26}$$

where $\hat{\mu}_{it} = \mu_{it} - \mu_{t-1}$ and $\hat{\mu}_{it-1} = \mu_{it-1} - \mu_{t-1}$.[5] The first term on the right is the effect of changes in within-firm markups; the next two terms capture the reallocation effects between firms in the industry; and the final two terms capture the effects of firm entry and exit. We label the sum of the second two terms the reallocation effect and of the final two terms the entry/exit effect.

It is useful to write the decomposition in growth rate form by dividing both sides of (26) by μ_{t-1} to obtain:

$$\begin{aligned}\frac{\Delta\mu_t}{\mu_{t-1}} = \frac{\sum_i \Delta\mu_{it} s_{it-1}}{\mu_{t-1}} + \frac{\sum_i \hat{\mu}_{it-1} \Delta s_{it}}{\mu_{t-1}} + \frac{\sum_i \Delta\mu_{it} \Delta s_{it}}{\mu_{t-1}} + \frac{\sum_{i\in Entry} \hat{\mu}_{it} s_{it}}{\mu_{t-1}} \\ + \frac{\sum_{i\in Exit} \hat{\mu}_{it-1} s_{it-1}}{\mu_{t-1}}\end{aligned} \tag{27}$$

[5] Following Haltiwanger (1997) and De Loecker et al. (2020), we de-mean by the appropriate aggregate (revenue weighted) level in order to correctly identify the role of the reallocation term.

In presenting our results on the evolution of the average markup, we can use (27) to define an index for the average markup set equal to 1 in the base period (period 0).

$$
\begin{aligned}
I^{\mu} = \prod_{t=1}^{T-1}\left(1+\frac{\Delta\mu_t}{\mu_{t-1}}\right) \\
&\approx \left[\prod_{t=1}^{T-1}\left(1+\frac{\sum_i \Delta\mu_{it}s_{it-1}}{\mu_{t-1}}\right)\right]\times\left[\prod_{t=1}^{T-1}\left(1+\frac{\sum_i \hat{\mu}_{it-1}\Delta s_{it}}{\mu_{t-1}}\right)\right] \\
&\times\left[\prod_{t=1}^{T-1}\left(1+\frac{\sum_i \Delta\mu_{it}\Delta s_{it}}{\mu_{t-1}}\right)\right]\times\left[\prod_{t=1}^{T-1}\left(1+\frac{\sum_{i\in Entry} \hat{\mu}_{it}s_{it}}{\mu_{t-1}}\right)\right] \\
&\times\left[\prod_{t=1}^{T-1}\left(1+\frac{\sum_{i\in Exit} \hat{\mu}_{it-1}s_{it-1}}{\mu_{t-1}}\right)\right],
\end{aligned}
\tag{28}
$$

where the approximation on the right-hand-side follows from ignoring (small) cross-product terms. In presenting our results, we combine the second and third terms and also the fourth and fifth terms to yield a threefold multiplicative decomposition involving the within-firm effect, the reallocation effect and the entry/exit effect.

2.4 Estimating the Parameters of the Firm Revenue Function

Although our specification of the revenue function (10) deals with the negative relationship between price and quantify for a firm with market power, estimating this function still faces the standard problem of correlation between input choices and the error term (see, e.g., Griliches and Marisse, 1996). We use the Blundell-Bond estimator (see Blundell and Bond, 1998, 2000) to consistently estimate the parameters of (10), from which we can infer estimates of the elasticity of substitution and the output elasticities we need to infer firm-level markups under our two alternative methods.

In applying the Blundell-Bond estimator, we allow for the possibility of adjustment costs in the setting of inputs,[6] productivity shocks that are serially correlated (which we model as AR(1)), and unobserved heterogeneity in productivity across firms. Letting $\theta_{it} = [\frac{(\eta-1)}{\eta}](\lambda_{it}+\omega_{it})$, we assume $\theta_{it} = \theta_i + v_{it}$, where $v_{it} = \rho v_{it-1} + \xi_{it}$ and ξ_{it}

[6] See Bond and Söderbom (2005).

is a zero mean random shock that is potentially correlated with input choices, assuming $0 < |\rho| < 1$. Lagging (10) by one period, multiplying the resulting equation through by ρ, and subtracting the result from (10) gives the quasi-differenced equation:

$$\begin{aligned} r_{it} - p_{Zt} \\ = \rho(r_{it-1} - p_{Zt-1}) + \tfrac{1}{\eta}\big((r_{Zt} - p_{Zt}) - \rho(r_{Zt-1} - p_{Zt-1})\big) \\ + \tfrac{(\eta-1)\beta_l}{\eta}(l_{it} - \rho l_{it-1}) + \tfrac{(\eta-1)\beta_k}{\eta}(k_{it} - \rho k_{it-1}) \\ + \tfrac{(\eta-1)\beta_k}{\eta}(k_{it} - \rho k_{it-1}) + \tfrac{(\eta-1)\beta_m}{\eta}(m_{it} - \rho m_{it-1}) + (1-\rho)\theta_i + \xi_{it} \end{aligned} \tag{29}$$

As is well known, the presence of firm fixed effects leads to a correlation between the lagged dependent variable and the error term ξ_{it} (Nickell, 1981). Input variables in the revenue equation will also be correlated with the error term where there are contemporaneous input responses to productivity shocks. One option for consistently estimating (29) is to take first differences and to instrument for the potentially endogenous right-hand-side variables. Blundell and Bond (1998, 2000) identify relatively mild initial conditions that allow lagged levels of the endogenous variables to be valid instruments for the endogenous first differences. However, Blundell and Bond (2000) also find that the lagged levels are weak instruments in a production-function-estimation setting. Alternatively, they suggest estimating a System GMM that includes the estimating equation in first differences and that equation in levels. Given its documented good performance in production function estimation, we adopt the Blundell-Bond System GMM estimator for estimation of our revenue function.[7]

3. Data

We construct a firm-level dataset that includes non-financial business firms in the UK in the Office for National Statistics (ONS) Annual Business Survey (ABS), covering the period 2008–2019. The ABS covers approximately two-thirds of UK non-financial

[7] As discussed in Coyle et al. (2023), the results are robust to using the ACF control function method of Ackerberg, Caves, and Frazer (2015) to estimate the parameters of the revenue function.

businesses, including firms' revenue, employment costs, capital expenditure and purchases of intermediates (materials).

To build the dataset, we implement the lowest local unit[8] in the data. We checked for duplication and removed 94 units from the sample. Building on Coyle and Mei (2023), we focus on the two sectors that made the biggest contribution to the post-2008 productivity growth slowdown in a sectoral decomposition: manufacturing (nineteen SIC2 subsectors with 148,962 observations) and information and communication (six SIC2 subsectors with 112,503 observations). This gives us an unbalanced panel with 261,465 observations from 2008-2019.

For each firm, there are data on total revenue, total employment, capital stock, and purchases of inputs. As all monetary values are in nominal terms, we employ the 2-digit industry-level ONS producer output price deflator and input price indices (manufacturing PPI and non-manufacturing SPPI) to deflate the nominal values to 2015 prices (in £ thousand).

We construct firm-level capital stocks using the Perpetual Inventory Method (PIM). One approach to identifying the initial level of capital stock for each firm is to use an estimate for total capital stock in the initial year, and allocate it according to firm-level revenue shares. However, this approach is problematic in our application because our dependent variable is a measure of firm-level revenue (Haskel and Martin, 2002; Harris and Moffat, 2017). We instead initialise the capital stock using the assumption that observed firm investment (measured net of disposals) is growing at the same rate prior to the appearance of a firm on our sample as we observe it to grow during the period it is observed in the sample. The initial capital stock for firm i in industry j, K_{ij0}, is then a depreciation-rate adjusted sum of all prior investments, where I_{ij0} is the (net) investment level of firm i in the first year, the firm appears in the sample. The initial capital stock is then given by the infinite series:

$$K_{ij,0} = \frac{I_{ij0}}{\left(1+\bar{g}_{ij}+\delta_j\right)} + \frac{I_{ij0}}{\left(1+\bar{g}_{ij}+\delta_j\right)^2} + \frac{I_{ij0}}{\left(1+\bar{g}_{ij}+\delta_j\right)^3} + \ldots, \tag{30}$$

[8] This follows a strand of literature, including Oulton (1998), Griffith (1999), Harris (2002), Harris and Robinson (2005), Harris and Moffat (2015), and Harris and Moffat (2017).

where $\bar{g}_{ij}$ is the firm-specific average growth rate of investment observed in the data, δ_j is the industry-specific deprecation rate and $\bar{g}_{ij} \times \delta$ is assumed to be a very small number and is ignored.[9] Multiplying both sides of the equation by $1/(1 + \bar{g}_{ij} + \delta_j)$ and subtracting the resulting equation from (1), we obtain:

$$K_{ij0} = \frac{I_0}{\bar{g}_{ij} + \delta_j}. \tag{31}$$

To estimate the capital stock for subsequent periods, we use the difference equation (consistent with (1)):

$$K_{ij(t+1)} = K_{ijt}(1 - \delta_j) + I_{ijt}. \tag{32}$$

The industry-specific value of δ_j is obtained from EU-KLEMS.[10] To obtain an estimate of $\bar{g}_{ij}$ used in the calculation of the initial capital stock for a given firm we use the first and last investment levels observed in the sample, which we label I_{ij0} and I_{ijd} respectively, where the number of periods between the first and last observation is τ_{ij}. The average growth rate is then calculated as:

$$\bar{g}_{ij} = \frac{lnI_{ijd} - lnI_{ij0}}{\tau_{ij}}. \tag{33}$$

4. Results

4.1 Baseline approach

We estimate firm-level markups based on Eqs. (11) and (19). As firm revenue shares (s_{it}) are small at both 2 and 3-digit levels (even at the SIC3-digit level the revenue

[9] Although this approach assumes that the firm exists in perpetuity, the effects of historically distant investments have negligible effects on the estimate of the initial capital stocks due to the growth rate and depreciation assumptions.

[10] We implement depreciation rates provided by the EU KLEMS database (from the additional variables column): http://www.euklems.net/.

share is only around 0.00098 on average, with standard deviation 0.0092),[11] so the difference in markups for each firm (under any assumption about competition) will be small. Hence, to provide more sensible analysis, we estimate our model specification using detailed SIC4-digit industry data.[12] Summary statistics are provided in Table 1. A clear pattern emerges. First, the table shows that average markup estimates are around 1.061 to 1.079 under SIC4. These numbers vary with different market structure assumptions; in all cases, the monopolistic competition markup (i.e., time-invariant within industry, see Eq. 19) is the lowest, whereas the Cournot (i.e., time-variant within industry, see Eq. 19) assumption gives the highest.

Figure 4 reports the evolution of our baseline measure of average Cournot markups across manufacturing firms over time. In the beginning of the sample period, markups were fluctuated, initially decreasing from roughly 1.2 in 2008 to 1.17 in 2009 and then increasing to about 1.27 in 2011. Since 2013 there has been a sharp decrease to below 1.16. In 2019, the average Cournot markup remained below 1.15, compared with above 1.2 in 2008.

While average markups provide informative headline, to fully capture the underlying distributional change in markups one should look at the evolution of the entire distribution of markups between 2008 and 2019. In doing so, we plot the kernel density of the unweighted markups for 2008 (black dash line) and 2019 (red solid line) in Figure 5. We find that the variance has slightly decreased, and the distribution has become more concentrated at the middle. The shift in the central region of the distribution provides evidence that more firms are gravitating towards median markups rather than experiencing an increase in markups. Even if the distribution of unweighted markups had remained unchanged, the weighted aggregate markup could have decreased if firms with higher markups now capture a smaller share of the market. This observation perhaps suggests that it is the middle portion of firms that is driving the decrease in average markups.

As flagged by Autor et al. (2020) and De Loecker et al. (2020), however, changes in aggregate markups are due to changes in unweighted markups and reallocation of

[11] We provide the distribution figures for the revenue weights between t and t-1 in Appendix Figures A1 and A2. We trim all right tail observation (i.e., revenue weight less than 0.000001 and 0.000002, respectively) in order to show the clear pattern (skewed to the left) through the weights.

[12] Note that when moving from the SIC2-digit to the SIC4-digit level, we extend from 38 broad SIC2 sectors to 385 subsectors. Foster, Haltiwanger, and Tuttle (2022) refer "less detailed" and "more detailed" estimates to ``2- digit'" and ``4-digit" level information.

economic activities, and so the average numbers do not fully capture the underlying distributional change. As in Haltiwanger (1997) and De Loecker et al. (2020), the unweighted markup change captures the average change attributed to a change in revenue-weighted markup while keeping the market shares (s_{it-1}) unchanged from last period, but the reallocation then captures the change in market share (Δs_{it}) and markup across firms (Δx_{it}). As noted in De Loecker et al. (2020), we include two additional terms to capture firms' entry and exit (see Eq. 26). Decomposing the average into within and reallocation effects helps us to understand better if firms' market power is changing over time.

Figure 6 plots the cumulative average markups index, taking into account firms' entry, exit, and reallocation, setting the initial level at 1 in 2008 throughout (see Eq. 28). First, we find that average revenue-weighted markups index in manufacturing declined from between 2008 and 2019, but with a notable rise in 2009 and 2010 (from around 0.97 to above 1.05). This increase is attributed to the reallocation term, which surged from below 1 to above 1.05, while the within-firm term remained relatively stable during this period. After 2011, we find that markups exhibit a downward trajectory until 2016, dropping from above 1.05 to below 0.95. The declining trend is driven mainly by the within term, fall by about 6% from 2011 to 2016.

The above finding is similar to Foster, Haltiwanger, and Tuttle (2022) who find that the reallocation and net entry terms dominate the change (increase) in markups in the US firms. In our case, we see an increasing trend of the reallocation term, which dampens the declining trend of the markup index.

In conjunction with UK manufacturing productivity, our results reflect the declining productivity trends among UK manufacturing firms highlighted in Coyle et al. (2024). Firstly, as illustrated in Figure 1, there is a negative correlation between firms' market share and productivity growth, indicating a potential convergence of UK manufacturing firms towards the middle portion of productivity. Secondly, as revealed in Figure 7, manufacturing firms' productivity has declined since 2008, with approximately a 12% fall by 2019. Consistent with our markup decomposition, the declining productivity is primarily driven by the within-term fall. The evidence suggests that the declining mark-ups observed here could is associated with the declining productivity trend, and a decrease in mark-ups may reflect a lack of intangible investment, depressed demand for high-skilled workers, resulting in lower quality goods. This finding is also consistent with Jacob and Mion (2022), in which they find that the weak productivity performance of UK firms post-recession is a consequence of the slowing down of demand that produces the decline in the evolution of markups and production scale.

4.2 Alternative Production Approach

Figure 8 shows results based on the alternative production approach. The trends are quite different with our demand approach, though the overall declining markups remain the same. First, we find that the within-term changes since 2008, with a declining trend from 2010 until 2019. Second, the reallocation term increases between 2010 and 2015. Third, the overall markup decreases but with a less steeply declining trend compared to our demand approach; throughout the period 2008-2019, the production approach markups fall by 2%, whereas our demand approach shows that the markups fall by 5%. One potential explanation for the difference between the two sets of estimates is that the implied output elasticity of variable input (β_{it}^{v}) with revenue share of variable expenditure (α_{it}^{v}) is used in the production approach's markup, whereas the elasticity substitution (η) with firm-level market share (s_{it}) is used in our structural approach's markups through market assumptions. As different variables are employed to capture markup dynamics, the slight differences are in line with expectations. Nevertheless, the overall declining trends remain similar.

Though the results between the structural and production approaches under our firm-level revenue function framework is broadly similar, in terms of the overall declining trend between 2008 and 2019, the results obtained form the production approach is by contrast different to the findings of Aquilante et al. (2019) and ONS (2022). By employing UK listed companies and production approach that follows closely the De Loecker et al. (2020) framework, they find large increases in manufacturing mark-ups from 1.35 in 2008 to 1.55 in 2015. However, rather than finding a rising trend of mark-ups, the ONS (2022) shows that mark-ups in UK manufacturing have been relatively flat since 1997. Perhaps the difference between each estimation framework obstacles the reconciliation of the markup trends. However, it is worth noting that the production approach that applies the general production function rather than the specific firm-level revenue function has received criticisms. For instance, Raval (2023) demonstrates the high sensitivity of inferred markups to the assumption about the flexible input – labour or materials – used in the calculation. Foster et al. (2022), even more striking, show that the US rising markup trend largely disappears when more granular data is used under production approach.

5. Discussion

By the end of 2019, the level of aggregate labour productivity in the UK was about a fifth lower than it would have been if the 1990-2007 trend had continued. This paper focuses on trends in markups in manufacturing, given the substantial role the sector has played in accounting for the UK's productivity growth slowdown. Using two distinct approaches, our results show that alongside a downward shift in the distribution of firm-level productivity there has been a decline in the average level and dispersion of mark-ups in the sector. We find a large decrease in sector-level gross markups of approximately five and two percentage points between 2008 and 2019 by two alternative methods. Both declines have been driven by the within component in the decomposition.

Our results contrast with results for the US that generally find rising markups in manufacturing and other industries, associated with rising concentration, increasing dispersion and the prominence of superstar firms. The contrasting decline in markups and increasing convergence among UK manufacturing firms is in line with broader evidence regarding the distinctive challenges and weaknesses within the UK manufacturing sector.

Our robust finding of declining markups, using different assumptions and methods, and combined with evidence on an adverse shift in firm-level total factor productivity, puts dynamics within UK manufacturing at the heart of the country's productivity puzzle. Such a fall in heterogeneity suggests different policy implications to those that would be suggested by a rise in heterogeneity driven by the rise of superstar firms. Much of the UK policy discussion has focused on how to improve the performance of lagging firms – the "long tail" – including policies to increase investment and improve the diffusion of knowledge from firms at the frontier.

While such policies are undoubtedly important, the observed "convergence to mediocrity" in UK manufacturing suggests the importance of improving the performance of firms in the upper part of the TFP distribution as well. These firms appear to be underperforming in global markets that are increasingly characterised by scale–based competitive advantage A relative underperformance could suggest polarisation among firms at the level of global competition, with the global frontier firms pulling ahead at the expense of leading UK firms, or the national economy failing to produce firms that succeed in scaling up in their international markets. On this view, the problem is not the presence of national superstars, but an absence of global superstars among UK firms. The mediocre middle is an uncomfortable position to occupy in global markets.

All Graphs and Tables

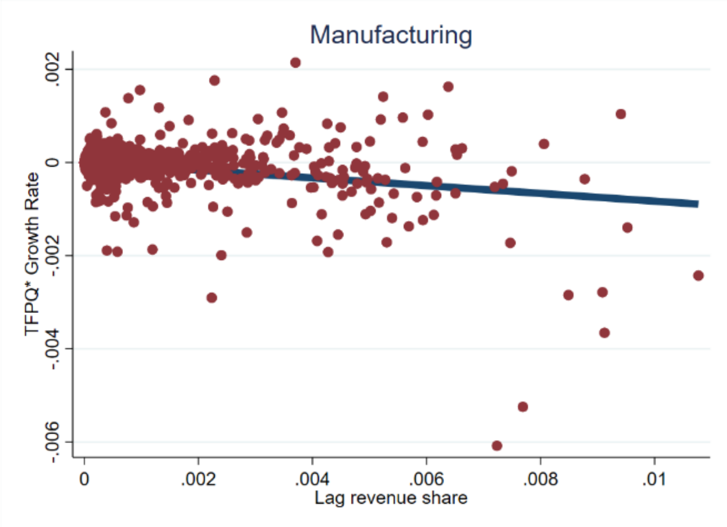

Figure 1. TFPQ* Growth vs Lag Revenue Share – Manufacturing

Source: Coyle et al. (2024).

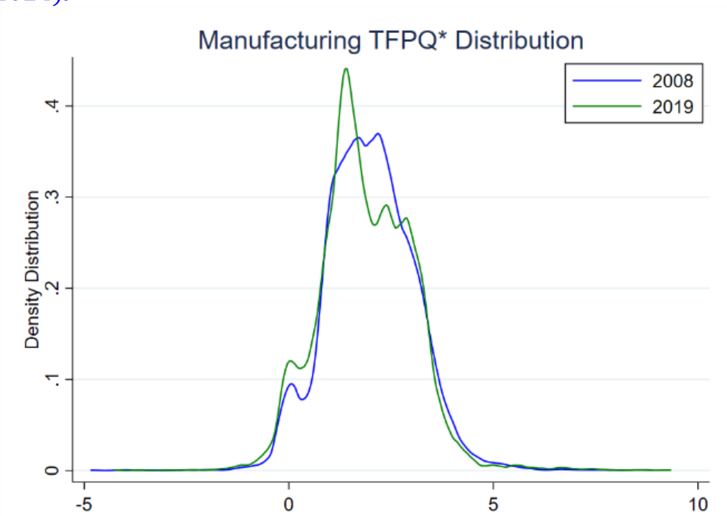

Figure 2: The Shift of Overall TFPQ* Distribution in 2008 and 2019 Manufacturing

Source: Coyle et al. (2024).

Table 1. Summary Statistics

	Mean (1)	Std. (2)	Obs. (3)
$1/\eta$	0.025	0.880	148,962
μ^M	1.061	0.200	148,962
μ^C	1.079	0.254	148,962

Notes: This table reports summary statistics through levels for each industry.

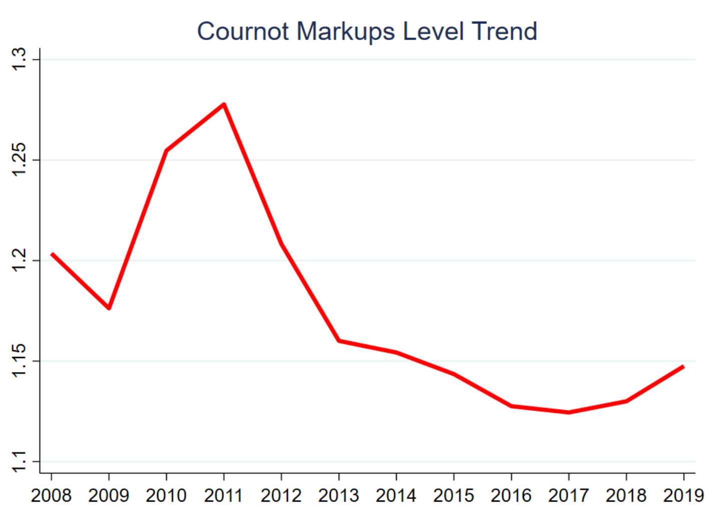

Figure 4. Average Cournot Markups

Notes: Elasticity substitution η from the estimated revenue function are sector-specific (four-digit). The average is revenue weighted. The figure illustrates the evolution of the average Cournot markup from 2008 to 2019.

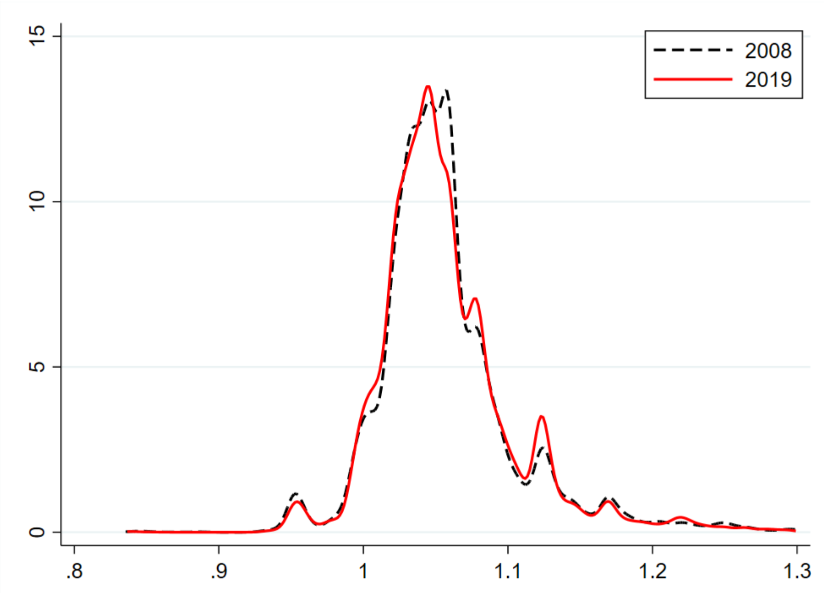

Figure 5: The Shift of Overall Cournot Markups Kernel Distribution in 2008 and 2019

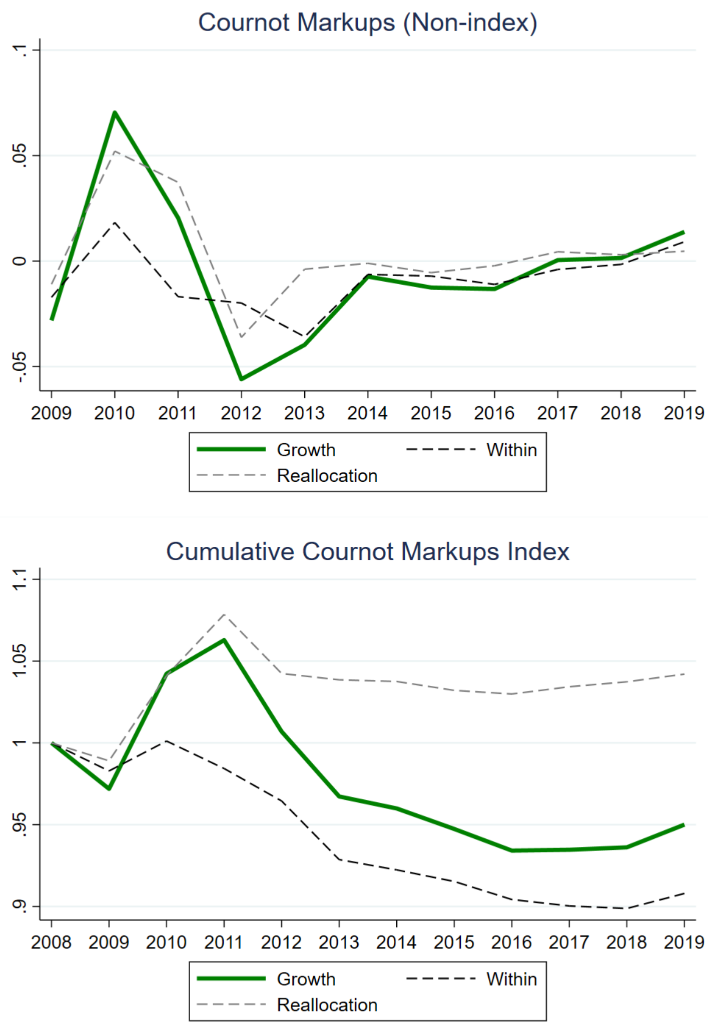

Figure 6. Non-index and Index Cournot Markups (2008 = 1)

Notes: The Markup index shows the evolution of a revenue-share weighted index of μ_t^{QC} between 2008 and 2019, where the value of the index is set equal to 1 in 2008. We have combined the reallocation and entry/exit terms into a single broad reallocation index.

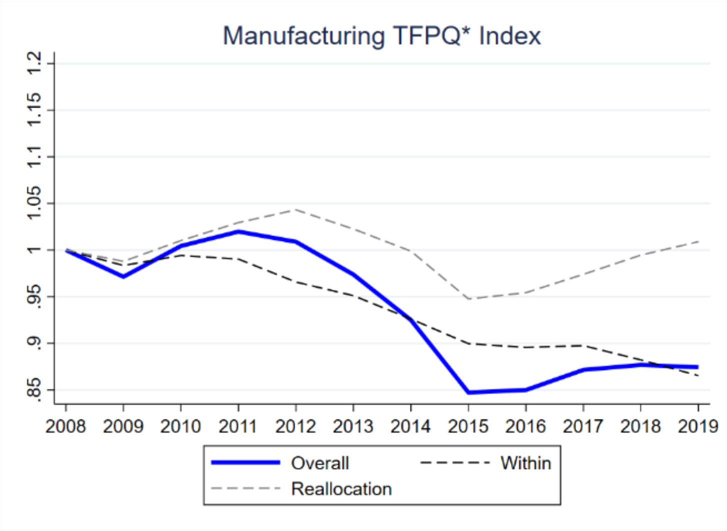

Figure 7. Baseline Decomposition of TFPQ* Index (2008 = 1)

Notes: The TFPQ* index shows the evolution of a revenue-share weighted index of TFPQ* between 2008 and 2019, where the value of the index is set equal to 1 in 2008. We have combined the reallocation and entry/exit terms into a single broad reallocation index.

Source: Coyle et al. (2024).

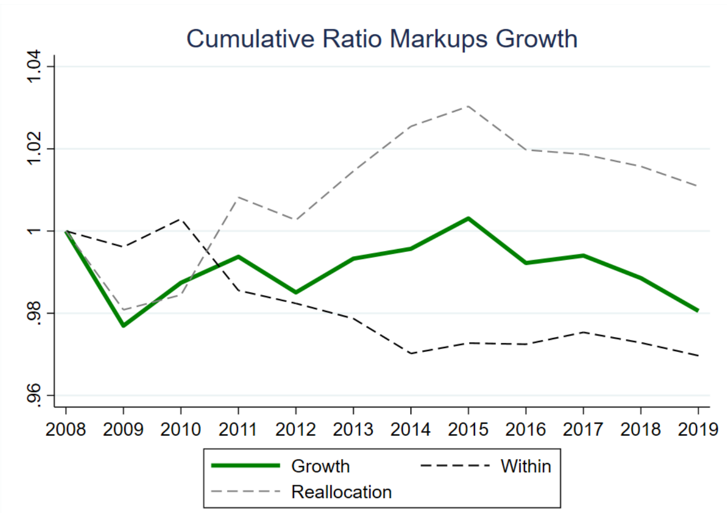

Figure 8. Revenue Weighted Markups (μ_t^{PA}) Growth Index (2008 = 1)

Notes: The Markup index shows the evolution of a revenue-share weighted index of μ_t^{PA} between 2008 and 2019, where the value of the index is set equal to 1 in 2008. We have combined the reallocation and entry/exit terms into a single broad reallocation index.

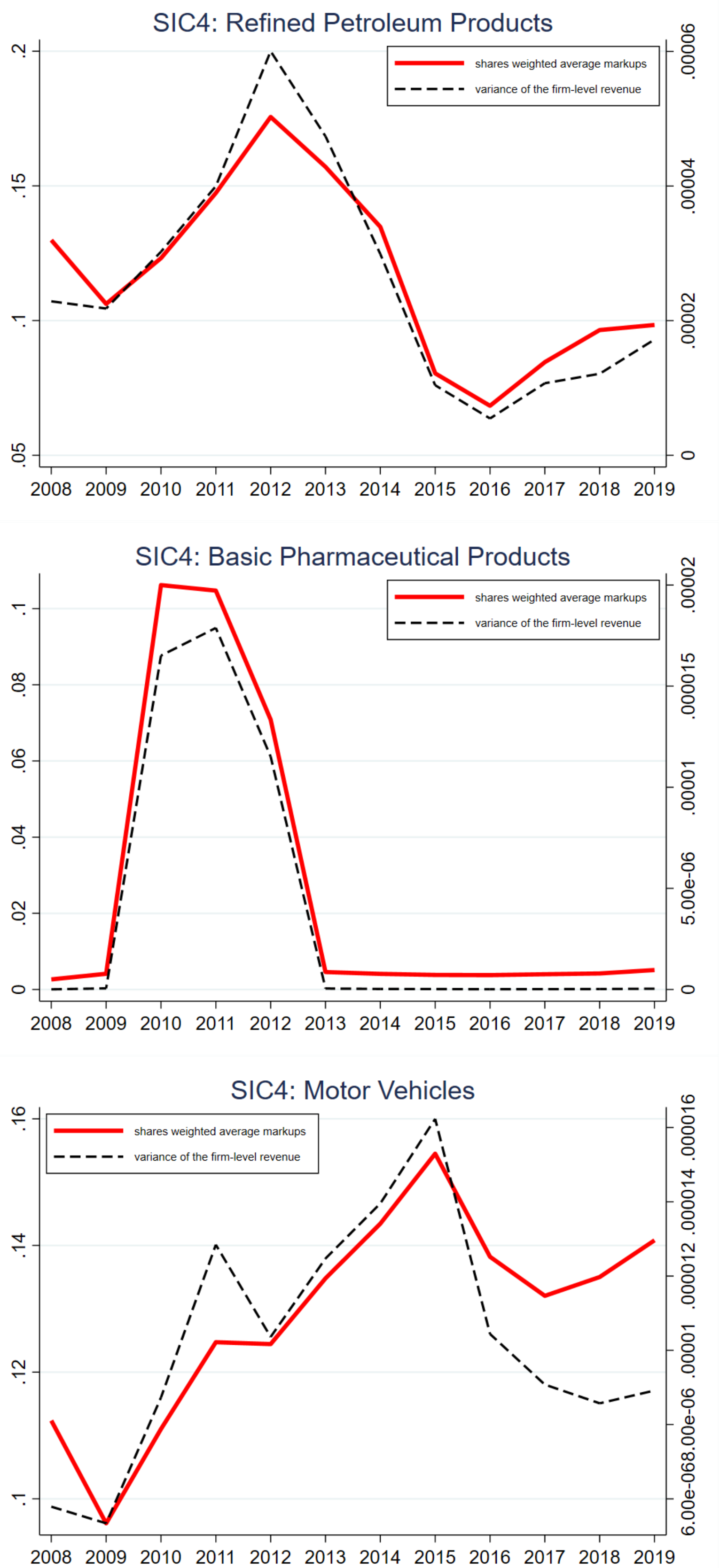

Figure 9. Revenue-share Weighted Average Markups vs Variance of the Firm-level Revenue Shares

Appendix I

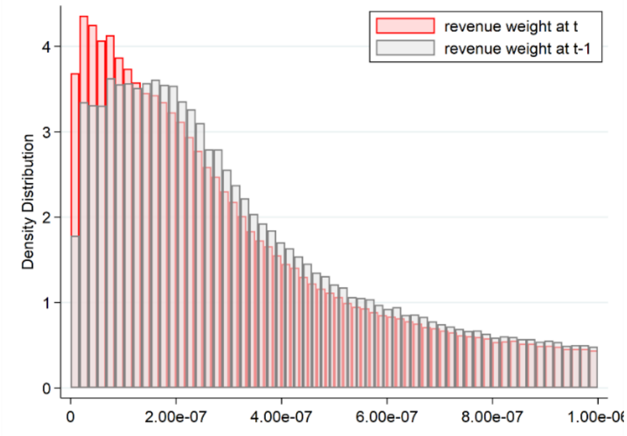

Figure A1. Revenue Weighted Distribution

Notes: The distribution is based on the 148,962 observations. We trim all right tile observation (revenue weight > 0.000001)

Sources: ONS ABS dataset and authors' own calculations.

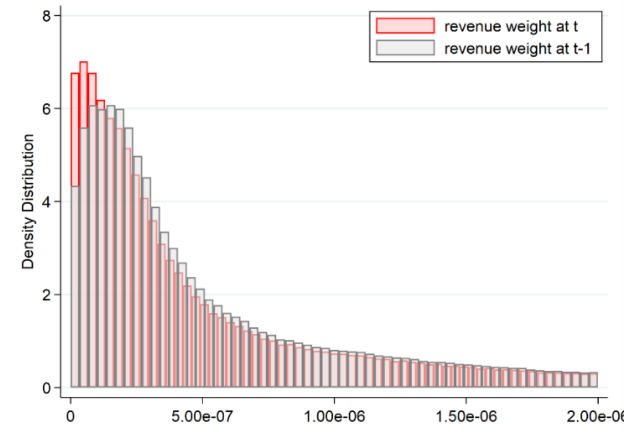

Figure A2. Revenue Weighted Distribution

Notes: The distribution is based on the 148,962 observations. We trim all right tile observation (revenue weight > 0.000001).

Sources: ONS ABS dataset and authors' own calculations.

Table A1. SIC4 Industry Classification

1011 Processing and preserving of meat	1712 Manufacture of paper & paperboard
1012 Proc and preserving of poultry meat	1721 Man & cont corrgatd pper & pperbrd
1013 Product of meat & poultry meat prod	1722 Manu of hhold & sanittoilet goods
1020 Proc fish, crustaceans & molluscs	1723 Manufacture of paper stationery
1031 Processing and preserving of potatoes	1724 Manufacture of wallpaper
1032 Manu of fruit & vegetable juice	1729 Man of othr art of ppr & pprbd nec
1039 Other proc & preserve of fruit & veg	1811 Printing of newspapers
1041 Manufacture of oils and fats	1812 Other printing
1051 Operate of dairies & cheese making	1813 Pre-press and pre-media services
1052 Manufacture of ice cream	1814 Binding and related services
1061 Manufacture of grain mill products	1820 Reproduction of recorded media
1062 Manu of starches & starch products	1920 Manu of refined petroleum prod
1071 Man bread, fresh pastry gds & cakes	2011 Manufacture of industrial gases
1072 Man ruskbiscpres pastry gdcakes	2012 Manufacture of dyes and pigments
1073 Man mac, nood, couscous & sim prod	2013 Manu of other inorganic basic chem
1081 Manufacture of sugar	2014 Manuf of other organic basic chem
1082 Man cocoa, chocolate & sugar conf	2015 Man fertilisers & nitro compounds
1083 Processing of tea and coffee	2016 Manuf of plastics in primary forms
1084 Manu of condiments & seasonings	2017 Manu synth rubber in primary forms
1085 Manu of prepared meals & dishes	2020 Manu of pest & other agrochem prod
1086 Man homogenic food preps & diet food	2030 Manu of paints & related products
1089 Manu other food products n.e.c.	2041 Man soap & detgt, clean & pol prep
1091 Manu preprd feeds for farm animals	2042 Man perfumes & toilet preparations
1092 Manufacture of prepared pet foods	2051 Manufacture of explosives
1101 Distil, rectifyg & blendng spirits	2052 Manufacture of glues
1102 Manufacture of wine from grape	2053 Manufacture of essential oils
1103 Manuf of cider & other fruit wines	2059 Manu of other chemical prod n.e.c.
1105 Manufacture of beer	2060 Manufacture of man-made fibres
1106 Manufacture of malt	2110 Manuf of basic pharmaceutical prod
1107 Manu soft drinks & mineral waters	2120 Man of pharmaceutical preparations
1310 Prep and spinning textile fibres	2211 Manu, retread of rub tyres & tubes
1320 Weaving of textiles	2219 Manufac of other rubber products
1330 Finishing of textiles	2221 Manu plastic plates, sheets, tubes
1391 Manu knitted & crocheted fabrics	2222 Manuf of plastic packing goods
1392 Manu made-up textile art, exc appl	2223 Manuf of builders? ware of plastic
1393 Manufacture of carpets and rugs	2229 Manuf of other plastic products
1394 Man cordage, rope, twine & netting	2311 Manufacture of flat glass
1395 Man non-woven & assoc art, ex appl	2312 Shapng & processing of flat glass
1396 Manuf of other tech & ind textiles	2313 Manufacture of hollow glass
1399 Manuf of other textiles n.e.c.	2314 Manufacture of glass fibres
1412 Manufacture of workwear	2319 Man & proc oth glas, inc tech glas
1413 Manufacture of other outerwear	2320 Manufacture of refractory products
1414 Manufacture of underwear	2331 Manuf of ceramic tiles and flags
1419 Man of other wearing apprl & acces	2332 Man of bricks, tiles & constr prod
1431 Man of knitted & crocheted hosiery	2341 Man of ceramic hhold & ornm artcls
1439 Man of othr knittd & crochetd appl	2342 Manu ceramic sanitary fixtures
1511 Tanning, dressng, dye of ltherfur	2343 Manu of ceramic inslts & inslg fit
1512 Man lug, hndbgs, sddlry & harness	2351 Manufacture of cement
1520 Manufacture of footwear	2362 Man plaster prod for constrcn purp
1610 Sawmilling and planing of wood	2363 Manuf of ready-mixed concrete
1621 Man ven sheets & wood-based panels	2364 Manufacture of mortars
1623 Manu of other builders	2365 Manufacture of fibre cement
1624 Manufacture of wooden containers	2370 Cutting, shaping & finishing stone
1629 Man oth prod of wood & plaitng mat	2391 Production of abrasive products

(continued)

Table 2. SIC4 Industry Classification

2399 Man of othr non-met min prod nec	2814 Manuf of other taps and valves
2410 Man basic iron, steel & ferro-ally	2815 Man bear,gear,grng & drvng elmnts
2420 Man holow prof & rltd fit of steel	2821 Man ovens, furnaces & furnace burn
2431 Cold drawing of bars	2822 Manu lifting & handling equipment
2433 Cold forming or folding	2823 Man off mchn & eqmt exc PC & acc
2434 Cold drawing of wire	2824 Manuf of power-driven hand tools
2441 Precious metals production	2825 Man non-dom cooling & ventiln eqmt
2442 Aluminium production	2829 Man other gen-purp machinry n.e.c.
2443 Lead, zinc and tin production	2830 Man agricultural & forestry mchnry
2444 Copper production	2841 Manuf of metal forming machinery
2445 Other non-ferrous metal production	2849 Manufacture of other machine tools
2451 Casting of iron	2891 Manuf of machinery for metallurgy
2452 Casting of steel	2892 Man mchnry for mng, quarr & constr
2453 Casting of light metals	2893 Man mcnry for food, bev & tob proc
2454 Casting of other non-ferrous metal	2894 Man mchn fr txt, app & leathr prod
2511 Manu of met structs & parts struct	2895 Man mchnry for pper & pprbrd prod
2512 Manu of doors and windows of metal	2896 Man plastics and rubber machinery
2521 Man cent heating radiators & boil	2899 Manu othr spec-purp mchnry n.e.c.
2529 Man oth tnks, resvrs & cont of met	2910 Manufacture of motor vehicles
2530 Manu of steam gen, exc CH boilers	2920 Man bodies for motr veh & trailers
2540 Manuf of weapons and ammunition	2931 Man electric eqmt for motor veh
2550 Forg,press,stamp & roll-form met	2932 Man othr parts & acc for motor veh
2561 Treatment and coating of metals	3011 Buildng of ships & floating struct
2562 Machining	3012 Buildng of pleasre & sportng boats
2571 Manufacture of cutlery	3020 Man railway loco & rolling stock
2572 Manufacture of locks and hinges	3030 Man air & spacecraft & rel mchnry
2573 Manufacture of tools	3040 Man of military fighting vehicles
2591 Man steel drums & sim containers	3091 Manufacture of motorcycles
2592 Manuf of light metal packaging	3092 Man bicycles & invalid carriages
2593 Man wire products, chain & springs	3099 Manf other transport eqmt n.e.c.
2594 Man fasteners & screw mchn prod	3101 Manuf of office and shop furniture
2599 Man other fabr metal prod n.e.c.	3102 Manufacture of kitchen furniture
2611 Manuf of electronic components	3103 Manufacture of mattresses
2612 Manuf of loaded electronic boards	3109 Manufacture of other furniture
2620 Man computers and peripheral eqmt	3212 Man jewellery & related articles
2630 Manuf of communication equipment	3213 Man imitation jewelry & rltd art
2640 Manuf of consumer electronics	3220 Manufacture of musical instruments
2651 Man instr for meas, testing & nav	3230 Manufacture of sports goods
2652 Manufacture of watches and clocks	3240 Manufacture of games and toys
2660 Manu of irradiation & electromed e	3250 Man med & dental instruments & sup
2670 Manu of opt instrmnts & photo eqmt	3291 Manufacture of brooms and brushes
2711 Manu of elect motors, gen & transf	3299 Other manufacturing n.e.c.
2712 Man elctrcty dist & cont apparatus	
2720 Manu of batteries and accumulators	
2731 Manufacture of fibre optic cables	
2732 Man oth elctrnc & elec wirescabls	
2733 Manufacture of wiring devices	
2740 Man of electric lighting equipment	
2751 Man of electrc domestic appliances	
2752 Man of non-electric domestic appl	
2790 Manu of other electrical eqmt	
2811 Man eng & turb, ex airvehcyc eng	
2812 Manufacture fluid power equipment	
2813 Manu other pumps and compressors	

Notes: The SIC4 industry classification follows the ONS Standard Industrial Classification (UK SIC 2007). See the link: ONS SIC 2007.

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