Recent Trends in Firm-Level Total Factor Productivity in the United Kingdom: New Measures, New Puzzles

Authors:

Diane Coyle[x]

University of Cambridge

John McHale[y]

University of Galway, Ireland

Ioannis Bournakis

SKEMA Business School and Université Côte d’ Azur, France

Jen-Chung Mei[x]

University of Cambridge

Date:

August 2023

The Productivity Institute

Working Paper No. 036

[x] Bennett Institute for Public Policy
[y] School of Business and Economics

Key words
Productivity, Quality, Manufacturing, ICT

JEL codes
D22, D24, D42, D43, E24, O47

Authors' contacts:
dc700@cam.ac.uk; john.mchale@universityofgalway.ie; ioannis.bournakis@skema.edu; jcm220@cam.ac.uk

Acknowledgements
We thank Joshua Abramsky, Matthew Agarwala, Bart Van Ark, Jonathan Haskel, Michela Vecchi, Katherine Robinson, Richard Heys, Giordano Mion, Raquel Ortega-Argiles, Skevi Pericleous, Tony Venables, ONS colleagues, and participants of the Productivity Institute Brown Bag Seminar,Productivity Institute 2022 Postdoc Workshop and Kingston University London Research Seminar for their helpful comments. Coyle is grateful for funding from the Productivity Institute, ESRC grant number ES/V002740/1, and Mei for funding from the Gatsby Charitable Foundation and the ONS small grant research support ONS2014988.

Suggested citation

D. Coyle, J. McHale, I. Bournakis, J. Mei (2023) *Recent Trends in Firm-Level Total Factor Productivity in the United Kingdom: New Measures, New Puzzles.* Working Paper No. 036, The Productivity Institute.

The Productivity Institute is an organisation that works across academia, business and policy to better understand, measure and enable productivity across the UK. It is funded by the Economic and Social Research Council (grant number ES/V002740/1).

The Productivity Institute is headquartered at Alliance Manchester Business School, The University of Manchester, Booth Street West, Manchester, M15 6PB. More information can be found on The Productivity Institute's website. Contact us at theproductivityinstitute@manchester.ac.uk

Abstract

Understanding the disappointing productivity performance of the UK economy since the financial crisis is complicated by the well-known challenges of estimating total factor productivity using revenue data. To address this, we develop a framework to estimate quality-adjusted total factor productivity based on a firm-level revenue function. Our structural identification relies on the inclusion of deflated industry revenue in the firm-level revenue function. Furthermore, as we allow quality changes to act as shift factors for firm-level demand, the resulting measure of total factor productivity combines product quality and technical efficiency components. We use the Blundell-Bond System GMM estimator to apply this structural identification technique to micro data for two important sectors of the UK economy – manufacturing and ICT – for the period 2008 to 2019. For manufacturing, we find a consistent fall in revenue-weighted within-firm quality-adjusted total factor productivity that is reinforced by adverse reallocation effects. For ICT, we find a small fall in within-firm quality-adjusted total factor productivity that is more than offset by favourable reallocation effects. These results are generally robust to imposing constant returns to scale on the production function and to allowing for a fixed component in labour costs. We conjecture that the declines in the within-firm component are explained by adverse relative quality effects for UK firms in international markets, rather than outright technological regression.

1. Introduction

By the end of 2019, nearly eleven years after the financial crisis, aggregate labour productivity in the UK was about a fifth lower than if the 1990-2007 trend had continued (ONS). The slowdown has been more pronounced in the UK than in other OECD economies. To explain this pattern, a number of authors, e.g., Coyle and Mei (2023), Goldin, Koutroumpis, Lafond, and Winkler (2022) and Fernald and Inklaar (2022), have found that the productivity puzzle can in large part be accounted for by productivity growth slowdowns in certain sectors: parts of manufacturing, information and telecommunications (ICT), electricity, transportation, and finance. At the same time, Andrews, Criscuolo, and Gal (2019) and Coyle, Lind, Nguyen, and Tong, (2022) highlight increasing heterogeneity among UK firms' productivity performance, a finding echoed for other OECD countries, with the most productive pulling increasingly far ahead of the remainder. The considerable amount of heterogeneity among firms (size, use of digital technology, R&D performance and export intensity) suggests that the exploration of the UK productivity puzzle in the post-2008 era must combine firm-level evidence with sectoral insights.

The objective of firm-level analysis is to map the within-sector productivity dispersion and obtain a consistent picture of the sources that drive productivity differences between firms. Among the explanations proposed are Harris and Moffat (2017), that identified poor productivity performance in the post-2008 period primarily as a service sector and small-firm phenomenon. Eckel and Neary (2010), Bernard, Redding, and Schott (2011), and Mayer, Melitz, and Ottaviano (2014) focuses on the within-firm productivity differences in skills, innovation status and export intensity that make firms concentrate on specific core product lines, which although offers less product variety, it increases productivity. It is this productivity dispersion across firms that drives cross-sectoral productivity differentials. Another strand of literature identifies market structure and rising markups as a key source of the observed productivity differentials across industries and/or firms (De Loecker and Eeckhout, 2021; De Loecker, Eeckhout, and Mongey, 2021). Accordingly, García-Perea, Lacuesta, and Roldan-Blanco (2021) for Spain, Autor, Dorn, Katz, Patterson, and Van Reenen (2020) for the US, suggest that productivity laggardness is driven by the growth of high-mark-ups of 'superstar' firms, while the majority of the remaining firms in the industry are small and unproductive.

Before looking into the underlying sources of productivity differentials, whether between firms or between sectors, we need to measure as accurately as possible the evolution of productivity using a framework that conforms to the pattern of the data. This is precisely the starting point of the present paper, which develops a new methodological framework to estimate total factor productivity (henceforth, TFP), of UK firms. We use data from two aggregate sectors previously identified as major contributors to the UK productivity slowdown (see, for instance, Coyle and Mei, 2023; Goodridge and Haskel, 2023).

There are, of course, well-known challenges in estimating production functions based on micro-data when, as in the UK, the available nominal input and output data must be deflated with industry price indices rather than specific firm-level prices and quantities (Griliches and Mairesse,1995; Klette and Griliches, 1996).[1] There is a large literature that developed estimation methods to overcome the problem of simultaneity bias between inputs selection and unobserved productivity shocks in estimating firms level production functions. Olley and Pakes (1996), Levinsohn and Petrin (2003), Ackerberg, Caves, and Frazer (2015), Bond, Hashemi, Kaplan, and Zoch (2021) and Sampi, Jooste and Vostroknutova (2021) propose semi-parametric estimation techniques to obtain consistent and unbiased measures of TFP.[2] Another important challenge in the measurement of TFP is to disentangle changes in revenue TFP due to changes in physical TFP and changes in quality that are reflected in prices. If quality differences are not taken into account, the true changes of physical TFP remains unclear as price markups evolve endogenously. The present paper recognises the importance of obtaining unbiased estimates of the parameters of the production function as well as of separating price effects from physical productivity changes and develops a novel measure of quality-adjusted[3] total factor productivity (henceforth, TFPQ) at firm and industry level (also see, Melitz, 2000). The novelty of our approach, given the absence of firm-level prices and volumes in UK micro data, is to develop a heterogeneous-firm model in which

[1] Also see Garcia-Marin and Voigtländer (2019), who raise the issue of the common use of revenue-based productivity that may lead to a downward bias in TFPR.

[2] The key characteristic of semi-parametric techniques is the use of a control function that approximates unobserved productivity shocks, using either data on investment (Olley and Pakes, 1996) or materials (Levinsohn and Petrin, 2003; De Loecker and Warzynski, 2012; Ackerberg, Caves, and Frazer, 2015).

[3] Note that the ``quality'' here is a shift factor for the representative consumer's inverse demand function for the good, implying that quality improvements result from changes to product characteristics that are valued by consumers (Fisher, 1965; Fisher and Shell, 1972; Muellbauer, 1975; Deaton and Muellbauer, 1980; Hulten, 1992; Fisher and Griliches, 1995). Please see section 3.1 for more details.

quality-adjusted volume-based TFP can be directly recovered from estimating a firm-level revenue function using deflated industry revenues and input expenditures.[4]

Our methodological approach provides new measures of firm- and industry-level TFPQ for manufacturing and ICT in the UK over the period 2008 to 2019. This methodology allows estimation of two different TFP measures – revenue-based TFP (TFPR) and quality-adjusted volume-based TFP (TFPQ*).[5] Throughout the paper, we present results from TFPQ*, which account for underlying quality differences.

The estimation of physical TFP from revenue data requires some functional form assumptions (Bond et al., 2021). Following the propositions of Klette and Griliches (1996) and DeLoecker (2011), we recover TFPQ* estimates under the assumption of constant elasticity of substitution (CES) for consumer preferences and Cobb-Douglas production technology. Central to this approach is to include in the firm-level revenue function the deflated industry revenue, which allows for the structural identification of the elasticity of substitution and consequently for the structural identification of TFPQ*.

Since firm-level revenue performance reflects both changes in product quality and technical efficiency, product quality can vary across firms and over time (Melitz, 2000). Without data on prices and quantities, TFP cannot be decomposed into into its quality and efficiency drivers, and presents an amalgam of quality and efficiency effects. The key contribution of our paper is to derive a TFP measure based on functional form assumptions that account for quality differences within the estimation framework of a revenue function. Therefore, our methodology is tractable for future applications with revenue firm level data, which is the empirical regularity in the literature.

After the structural identification of TFPQ* through the industry revenue function, we still encounter the challenge of recovering consistent estimates for the parameters of the revenue function. For this, we adopt the System GMM estimator of Blundell and Bond (1998, 2000).[6,7] .. Although this estimator method performs well on our data in

[4] The use of the industry-level price index is a challenge for our framework in cases that firms within-industries produce heterogeneous products and face different output prices (Melitz, 2001; De Loecker, 2011).

[5] Being different to the existing literature, we label our quality-adjusted TFP as TFPQ* instead of TFPQ, as our measure takes into account both product quality and technical efficiency components. Please see section 3 for more details.

[6] See, Blundell and Bond (2000) for an application of the extended GMM method for estimating production functions. Bond et al. (2021) discuss an application for estimating revenue functions.. In our framework, the revenue function is estimated as a system of the level of the first differenced revenue equation.

[7] Following Bond and Söderbom (2005), we also assume that all inputs are subject to adjustment costs.

recovering estimates of the relevant elasticities, we confront the common problem of low implied output elasticities for capital.[8] As a robustness check, we estimate the model under the assumption of constant returns to scale (CRS), deriving the output elasticity of capital as a residual of output minus the weighted contribution of labour and materials. Furthermore, we estimate a version of the model that allows a fixed-cost component in labour input.[9]

The estimates from our analytical framework reveal that within-firm changes in manufacturing are the primary drivers of the UK productivity slowdown for 2008-2019.[10] We show that the level trend of revenue-weighted average TFPQ* for manufacturing slows down after 2008, before recovering somewhat in 2018. The opposite is true for ICT, where TFPQ* grew over the period 2008-2019.[11] After controlling for firm entry and exit dynamics and the reallocation of economic activity towards high-productivity firms through TFPQ*, we show that manufacturing drives the overall UK productivity slowdown, with a steep decline in the 'within' firm component after 2008 compounded by a negative effect from reallocation. For ICT, a post-2008 slowdown in the within component is offset by reallocation effects.

Furthermore, we find that the distribution of firms' quality-adjusted TFPQ* shifts downwards in manufacturing and upwards in ICT between 2008 and 2019. We also account for outliers other aspects that are likely to influence the growth of TFPQ* in different ways across sectors. We find that removing 'zombie' firms does not alter the findings, nor do the results differ substantially by ownership status – domestically-owned, foreign-acquired or foreign-owned – in both sectors. The robust but puzzling finding of declining within-firm quality-adjusted TFP, albeit with contrasting reallocation effects in manufacturing and ICT, indicates that UK firms are very likely poor performers in quality competition in international markets.

---

[8] For instance, De Loecker and Goldberg (2014) table 2 reports low estimated (both revenue and output) elasticity of capital. Klette and Griliches (1996) table 2 also provides low estimated output elasticity of capital.

[9] Reflecting our allowance for variable quality, such fixed costs may reflect investments in quality improvements, which we assume are common across firms in an industry.

[10] Following Bond et al. (2021), our estimation strategy relies on the system Generalised Method of Moments (system GMM) estimator that assumes the (combined) productivity shock follows a low-order linear AR process (see Blundell and Bond (1998, 2000) for theory, and Orr (2022) for a recent empirical implementation). We provide an alternative check by using ACF (Ackerberg, Caves, and Frazer, 2015) control function method and we find our results consistent.

[11] Additionally, we find that manufacturing has the lowest level of TFPQ* (and so TFPR too) since 2008.

The rest of the paper proceeds as follows. Section 2 provides literature review, and Section 3 sets out the model framework and estimation methodology. Data are discussed in section 4 and estimates are presented in section 5. Section 6 presents robustness analyses. Section 7 discusses the findings in the context of the literature and concludes.

2. Previous literature

Our paper contributes to the existing literature in two ways. First, we contribute to the agenda seeking to understand the UK productivity slowdown by providing firm-level evidence from two major sectors that are key components in the evolution of aggregate productivity. Our work is placed in a comparative context and helps draw insights regarding the relative performance of different sectors in the UK economy. Second, we develop a framework that allows us to produce aggregate revenue-based TFP as well as generate TFP measures that accommodate product quality differences. We implement the latter adjustment without data on unit-specific prices, which are rarely available at the firm level. Therefore, our model maintains a high degree of tractability and should be helpful for future studies that seek to derive TFP measures consistent with quality differences across industries and firms.

This paper is closely related to Forlani, Martin, Mion, and Muûls (2022) and Jacob and Mion (2022). Using separate firm-level price and quantity data, Forlani, Martin, Mion, and Muûls (2022) develop a novel framework to recover heterogeneity in demand and quantity TFP across Belgian firms. They find that physical TFP and demand are negatively correlated. Jacob and Mion (2022) define revenue TFP as price multiplied by physical TFP, and total revenue is then this product times an input index. Looking at the weak UK productivity performance since 2008 they find demand and decreasing physical TFP as the determinants that push down revenue TFP (and labour productivity). Although the overall finding is similar to ours, we treat differently the input price index in our specification. We also take into account the effect on output price (and thus on revenue) as the firm increases its input use assuming that the firm must lower its price to sell an additional unit of output produced with additional inputs. Analogously, we identify revenue based TFP as the multiplicative constant in the revenue function.

Our results also add to the recent literature on the UK productivity slowdown post-2008. Coyle and Mei (2023) explore the slowdown in sectoral-level labour productivity growth in the UK from 2008 to 2019 and find that the within-industry contribution slowdown is the main source of the UK labour productivity slowdown post-2008. Providing an international comparative perspective on the UK productivity slowdown, Fernald and Inklaar (2022) show a common slowdown in TFP growth across OECD economies since 2007. Focusing on the UK productivity puzzle between 2008 and 2012, Harris and Moffat (2017) show that the slowdown in UK's service sector TFP can be accounted for by a large negative TFP shock in 2008. Growth accounting studies with national accounts data have also been applied to understanding the UK productivity puzzle (Goodridge, Haskel, and Wallis, 2013, 2018). These findings indicate that the TFP puzzle is attributed to the labour productivity puzzle. Unlike the previous papers, we develop a novel model to examine aggregate quality-adjusted TFP in the UK post-2008.

3. Framework for Estimating TFP

This section develops a simple structural model with heterogeneous firms that allows, in principle, for the estimation of quality-adjust TFP from an estimated firm-level revenue function. Our setting is an economy with a large number of heterogeneous, imperfectly competitive firms using Cobb-Douglas production technologies, classified into a number of sectors, and a representative consumer with CES preferences over the quality-adjusted products of these firms. In setting out the model, we assume for simplicity that there are just two sectors.

3.1 Firm-Level Revenue Function

The representative consumer has a Cobb-Douglas utility function over an index of manufactured goods, Z_t, and an index of services, X_t:

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

Since utility is assumed 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.

We next derive the demand curves facing individual firms. We set this out for manufacturing; an identical analysis applies for other sectors. Aggregate output is a 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 (where quality improvements result from changes to product characteristics that are valued by consumers), 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 output index. 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 $Q_{it}^{*} = \Lambda_{it}Q_{it}$.[12] We assume that $\eta > 1$ and that each firm produces a single product variety. Given the allocation of income to manufacturing goods, we can derive the demand function facing a given firm producing a good with quality Λ_{it} as:

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

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

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

From (6), we can see that quality improvements reflect 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. 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

[12] 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). Fisher and Shell (1972, Essay I) is a classic reference on the restrictions on utility functions required for quality change to be represented as the equivalent of "repackaging" and thus a "better is more" formulation. Muellbauer (1975) identifies the importance of homothetic preferences for this formulation. Deaton and Muellbauer (1980) discuss the relationship between hedonic methods of measuring quality change and utility-based measures of quality change (see also, Fisher and Griliches, 1995). For our analysis, we make the strong assumption that quality changes are accurately captured in the calculation of industry price indexes. As discussed below, we also allow from the relevant "quality" changes can reflect relative as well as absolute quality changes. In addition to being reflected in the price index, the key requirement is that the "quality" change acts as a shift factor for the representative consumer's inverse demand function for the good.

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.

Turning to production side of the economy, we assume each firm has the Cobb-Douglas production function:

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

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.

In order to derive the revenue function it is useful to 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 $R_{Zt}{=}P_{Zt}Z_t = \alpha\, P_t Y_t$.

We next define our measure of revenue-based total factor productivity (TFPR).[13] We denote TFPR for firm i in period t as Ψ_{it}. Using the analogy with the representation

[13] There are several definitions of TFPR in the literature. In the context of a model without quality change, Hseih and Klenow (2009) define TFPR as TFP multiplied by price and show that under certain conditions TFPR does not vary with TFP. However, one possibly undesirable feature in some contexts is that TFPR is affected by input use as increased output will imply a lower price as firms move down their demand curves to sell the larger quantity. Therefore Blackwood et al. (2017) employ the intuitive approach of identifying TFPR as the residual from an estimated revenue function and label this TFP^{rr} (where rr denotes regression residual) and where the relevant elasticities used to identify TFP^{rr} are revenue elasticities and not output elasticities. Under this approach, TFP^{rr} depends on various "fundamentals," that in our setting include product quality, technical efficiency, the elasticity of product substitution and deflated industry revenue.

of technical progress in a production function, we identify Ψ_{it} based on a general multiplicative form of the revenue function:

$$R_{it} = \Psi_{it} G(L_{it}, K_{it}, M_{it}) . \tag{10}$$

Given the specific form of the revenue function (9), we can thus identify TFPR as:

$$\Psi_{it} = (\Lambda_{it}\Omega_{it})^{\frac{\eta-1}{\eta}} \left(\frac{R_{Zt}}{P_{Zt}}\right)^{\frac{1}{\eta}}. \tag{11}$$

From (9), we see that 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:

$$r_{it} - p_{Zt} = \frac{1}{\eta}(r_{Zt} - p_{Zt}) + \frac{(\eta-1)\beta_l}{\eta} l_{it} + \frac{(\eta-1)\beta_k}{\eta} k_{it} + \frac{(\eta-1)\beta_m}{\eta} m_{it} + \frac{(\eta-1)}{\eta}(\lambda_{it} + \omega_{it}) \tag{12}$$

where lower case letters represent the natural log of a variable. A critical feature of (12) is that identification of η is possible from the estimated coefficient on the deflated-industry-revenue variable in the estimated revenue equation (Griliches and Klette, 1996). The natural log of TFPR is identified as:

$$\begin{aligned}\psi_{it} &= \frac{(\eta-1)}{\eta}(\lambda_{it} + \omega_{it}) + \frac{1}{\eta}(r_{Zt} - p_{Zt}) \\ &= r_{it} - p_{Zt} - \left(\frac{(\eta-1)\beta_l}{\eta} l_{it} + \frac{(\eta-1)\beta_k}{\eta} k_{it} + \frac{(\eta-1)\beta_m}{\eta} m_{it}\right).\end{aligned} \tag{13}$$

Furthermore, the natural log of TFPQ* (which includes both product quality and technical efficiency components) is:

$$\lambda_{it} + \omega_{it} = \frac{\eta}{\eta-1}\psi_{it} - \frac{1}{\eta-1}(r_{Zt} - p_{Zt}). \tag{14}$$

Given an estimate of η it is thus possible to identify both TFPR and TFPQ* from revenue and input data. It is also possible to obtain estimates of the relevant output elasticities for the different inputs from the estimates of the revenue elasticities of those estimates and an estimate of the elasticity of substitution. From an inspection of (13), note that the estimated value of TFPR will be close to the estimated value of TFPQ* when the estimated elasticity of substitution, η, is high. As we find a high estimate of η in our empirical application, we will report only the results for TFPQ* in our main analysis.

Finally, using our definition of quality-adjusted output and the production function, we can write the quality-adjusted production function in logs as:

$$q^*_{it} = \lambda_{it} + \omega_{it} + \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it}, \tag{15}$$

where $q^*_{it} = \lambda_{it} + q_{it}$. Under our assumptions, we are therefore able to estimate the key parameters of the quality-adjusted production function using deflated industry revenue and input expenditure data, although it is not possible to separate out the quality and technical efficiency components of TFPQ*.

3.2 Estimation Strategy

Our assumed empirical setting allows for the possibility of adjustment costs in the setting of all inputs,[14] TFPQ* shocks that are serially correlated (which we model as AR(1)), and unobserved heterogeneity in TFPQ* across firms. However, along with the adjustment costs, we allow input choices respond to contemporaneous TFPQ* shocks, so consistent estimation of the revenue function faces the challenges of both unobserved heterogeneity and simultaneity that are common in the production function estimation literature (see, e.g., Griliches and Marisse, 1996).

Letting $\theta_{it} = [\frac{(\eta-1)}{\eta}](\lambda_{it} + \omega_{it})$, we thus assume:

$$\theta_{it} = \theta_i + v_{it}, \tag{16}$$

where

$$v_{it} = \rho v_{it-1} + \xi_{it}. \tag{17}$$

ξ_{it} is a zero mean random shock that is potentially correlated with input choices and we assume $0 < |\rho| < 1$. Lagging (12) by one period, multiplying the resulting equation through by ρ, and subtracting the result from (12), gives the quasi-differenced equation:

$$\begin{aligned} & r_{it} - p_{Zt} \\ &= \rho(r_{it-1} - p_{Zt-1}) + \frac{1}{\eta}\big((r_{Zt} - p_{Zt}) - \rho(r_{Zt-1} - p_{Zt-1})\big) \\ &+ \frac{(\eta-1)\beta_l}{\eta}(l_{it} - \rho l_{it-1}) + \frac{(\eta-1)\beta_k}{\eta}(k_{it} - \rho k_{it-1}) \\ &+ \frac{(\eta-1)\beta_k}{\eta}(k_{it} - \rho k_{it-1}) + \frac{(\eta-1)\beta_m}{\eta}(m_{it} - \rho m_{it-1}) + (1-\rho)\theta_i + \xi_{it}. \end{aligned} \tag{18}$$

The presence of the firm fixed effect 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

[14] See Bond and Söderbom (2005).

input responses to TFPQ* shocks. One option for consistently estimating (18) is to take first differences and instrument for potentially endogenous right-hand-side variables. Blundell and Bond (1998, 2000) identify relatively mild initial conditions that allow lagged levels of endogenous variables to be valid instruments for the endogenous first differences. However, Blundell and Bond (2000) find that lagged levels provide 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. Moreover, they again provide relatively mild initial conditions under which lagged first differences are valid instruments for the endogenous variables in the levels equation. They show that the System GMM provides more efficient estimates than a single equation approach. Given the superiority of the System GMM estimator in the context of a production function set-up, we adopt the Blundell-Bond System GMM estimator for parameters of the revenue function (Blundell and Bond, 1998, 2000).[15]

3.3 TFP Growth Decomposition

At the sector level, we first show the evolution of an index of revenue-share-weighted TFPQ* that is set equal to 1 in the first year of our sample. Moreover, following the approach of De Loecker et al. (2020), we decompose the evolution of that index into the product of an index of within-firm TFPQ*, an index of reallocation effects, and an index of entry and exit effects.

Letting this index be x_t (measured in logs), we express it as a revenue-share-weighted average of the corresponding firm-level measures:

$$x_t = \sum_i x_{it} S_{it}, \tag{19}$$

where S_{it} is the share of firm i in the total revenue of the industry in time t and x_{it} refers to our firm-level TFPQ*. Using the DeLoecker et al. (2020) decomposition, we can write the *growth rate* of the aggregate (approximated as the log difference) as *sum* of a number of components:

$$\Delta x_t = \sum_i \Delta x_{it} S_{it-1} + \sum_i \hat{x}_{it-1} \Delta S_{it} + \sum_i \Delta x_{it} \Delta S_{it} + \sum_{i \in Entry} \hat{x}_{it} S_{it} + \sum_{i \in Exit} \hat{x}_{it-1} S_{it-1}, \tag{20}$$

[15] Our results are independent on the method employed. As a useful additional check, we run the ACF control function method (Ackerberg, Caves, and Frazer, 2015), which corrects the issue of functional dependence at the first stage of Levinsohn and Petrin (2003) by estimating an equation that identifies the labour coefficient. We test if our main TFP results are robust to the use of the ACF estimation framework. Appendix I Figures AI 1 and 2 indicate that results from both estimations follow a very similar trend.

where $\hat{x}_{it} = x_{it} - x_{t-1}$ and $\hat{x}_{it-1} = x_{it-1} - x_{t-1}$.[16]

The first term on the right is the effect of within-firm productivity growth on the aggregate growth rate. The next two terms capture reallocation effects between firms in the industry, and the final two terms capture the effects of firm entry and exit. We term the sum of the second two terms the reallocation effect and the final two terms the entry/exit effect. The final four terms can be collectively thought of as a broad reallocation effect. Finally, setting the relevant level of the index equal to 1 in the first year of the sample, we use the relevant calculated weighted growth rates to infer the evolution of the level of the index over the sample. We present these index evolutions at the sector level.

4. Data

We construct a firm-level dataset that includes non-financial business firms in the UK in the Annual Business Survey, (ABS) covering the period 2008–2019. The ABS covers approximately two-thirds of UK non-financial businesses, including firms' revenue, employment costs, capital expenditure and intermediates purchases.

To build the dataset, we implement the lowest local unit[17] in the data – firm-level. We checked for duplication and removed 94 units from the sample. Building on Coyle and Mei (2023),[18] we focus on firms in two sectors that account the most for the post-2008 productivity 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 throughout 2008-2019.[19]

[16] 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.

[17] Following Harris and Robinson (2002), we proceed at the firm-level by using the Annual Business Survey (ABS) 2008-2019, also used by other studies (Oulton, 1997; Griffith, 1999; Harris, 2002; Harris, 2005a; Harris and Moffat, 2015; and Harris and Moffat, 2017). While the establishment unit is also available, an establishment is not an economic unit but an accounting unit that often gains and loses local units as enterprises respond to ONS requests for information (Harris and Robinson, 2002). As companies open and/or close, or buy and/or sell firms, the number of local units covered by an establishment, and firms' sizes and vintages, would change over time, which makes it difficult to undertake certain types of analysis in an economically meaningful way. This issue has been highlighted in Harris and Drinkwater (2000), Harris and Robinson (2002), and Harris (2002) in which the authors provide evidence on how unstable establishments, in terms of compositional changes, are over time.

[18] Coyle and Mei (2022) identify six industries that cause the UK productivity slowdown. While the present work narrowly focuses on manufacturing and information and communication, we provide results across the six industries in appendix.

[19] While our main context focuses only on manufacturing and information and communication, we also estimated results (provided in Appendix) for electricity (four SIC2 subsectors with 132,170 observations),

For each firm, there is data on total revenue, total employment, capital stock, and purchases of inputs. As all 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) and annual estimates of gross and net capital stocks and consumption of fixed capital in the UK to adjust (deflate) the nominal value at 2015 prices (in £ thousand). We also construct firm-level capital stocks using the Perpetual Inventory Method (PIM). The PIM estimates the current period's capital stock based on the prior period's capital stock, with an assumption about depreciation rates, and the current period's investment:

$$k_{it} = k_{t-1}(1-\delta) + inv_{it}$$

where inv_{it} is defined as the sum of expenditures on land, building, vehicle, and other fixed capital, and δ is the rate of physical depreciation as it is provided by the EU-KLEMS.[20] While the ABS provides capital stock information, there are two issues. First, there is no data on the initial capital stock. Secondly, there is missing data for many firms. To apply the PIM to construct the capital stock across firms, we first generate the initial capital stock of each firm by the first year each firm appears in the ABS dataset. To generate the initial capital stock, we use ONS sectoral level aggregate capital stock and investment,[21] allocated to each firm, weighted by the revenue share in total sectoral revenue (Martin, 2002; Harris and Moffat, 2017).

5. Baseline Results

We use data as described from the ONS Annual Business Survey of UK firms and to estimate TFPR and TFPQ* over the period 2008-2019. Our framework allows us to assess variations of TFPQ* between-firm and within-industry in the sectors of Manufacturing and ICT, which have been previously identified as accounting substantially for the aggregate productivity slowdown in this period.

---

wholesale trade and retail (three SIC2 subsectors with 1,263,806 observations), transportation (five SIC2 subsectors with 171,769 observations), and finance (one SIC2 subsector with 6,528 observation). With all six industries included, our sample contains 458,548 firms and 1,847,603 observations throughout the period 2008-2019. This unbalanced panel data thus contain 60,595 firms observed every year, and 397,953 firms are observed for at least one year.

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

[21] Aggregate gross and net capital stocks: https://www.ons.gov.uk/economy/grossdomesticproductgdp/datasets/businessinvestmentbyindustryandasset; and aggregate business investment: https://www.ons.gov.uk/economy/nationalaccounts/uksectoraccounts/datasets/grossandnetcapitalstocksfortotaleconomybyindustryandassetincurrentpricesandchainedvolumemeasures

Table 1a. Manufacturing Implied CRS (firm-level average)

	$1/\eta$ (1)	$(\eta/\eta-1)\beta_m$ (2)	$(\eta/\eta-1)\beta_k$ (3)	$(\eta/\eta-1)\beta_l$ (4)	β_m (5)	β_k (6)	β_l (7)	RS (8)
SIC10	0.098***	0.542***	0.006***	0.221***	0.488	0.005	0.199	0.69
(Food Products)	(0.010)	(0.049)	(0.002)	(0.045)				
SIC11	0.067***	0.381***	0.005	0.542***	0.355	0.004	0.505	0.86
(Beverages)	(0.025)	(0.045)	(0.010)	(0.106)				
SIC13	0.092***	0.307**	0.019	0.628***	0.278	0.018	0.570	0.87
(Textiles)	(0.019)	(0.148)	(0.037)	(0.186)				
SIC16	0.069***	0.309***	-0.019	0.513***	0.288	-0.017	0.477	0.75
(Wood Products)	(0.028)	(0.100)	(0.041)	(0.068)				
SIC17	0.042***	0.099**	0.013**	0.826***	0.095	0.012	0.791	0.90
(Paper Products)	(0.014)	(0.048)	(0.007)	(0.055)				
SIC18	0.061***	0.149***	0.016***	0.688***	0.140	0.015	0.645	0.80
(Printing & Reproduction)	(0.012)	(0.053)	(0.006)	(0.077)				
SIC20	0.100***	0.529***	-0.0007	0.147***	0.476	-0.0007	0.132	0.61
(Chemicals)	(0.017)	(0.080)	(0.005)	(0.044)				
SIC22	0.036***	0.741***	-0.012***	0.309***	0.714	-0.012	0.297	1.00
(Rubber & Plastic)	(0.008)	(0.095)	(0.005)	(0.108)				
SIC23	0.069***	0.517***	-0.012***	0.488***	0.481	-0.011	0.454	0.92
(Non-Metallic Mineral)	(0.004)	(0.032)	(0.004)	(0.029)				
SIC24	0.095***	0.422***	-0.005	0.405***	0.382	-0.005	0.366	0.74
(Basic Metals)	(0.037)	(0.092)	(0.005)	(0.120)				
SIC25	0.080***	0.347***	0.008	0.590***	0.318	0.007	0.543	0.87
(Fabricated Metal)	(0.009)	(0.081)	(0.005)	(0.098)				
SIC26	0.096***	0.268***	-0.010	0.561***	0.242	-0.009	0.507	0.74
(Comp., Elec. & Optical)	(0.021)	(0.063)	(0.007)	(0.085)				
SIC27	0.095***	0.393***	-0.002	0.449***	0.356	-0.002	0.407	0.76
(Electrical Equipment)	(0.018)	(0.075)	(0.006)	(0.120)				
SIC28	0.109***	0.298***	-0.002	0.608***	0.265	-0.002	0.541	0.80
(Machinery and Eqp. n.e.c.)	(0.013)	(0.053)	(0.004)	(0.063)				
SIC29	0.032***	0.456***	0.001	0.502***	0.441	0.001	0.486	0.93
(Motor Vehicles)	(0.013)	(0.066)	(0.004)	(0.062)				
SIC30	0.035	0.432***	-0.004	0.602***	0.417	-0.004	0.581	0.99
(Other Transport Eqp.)	(0.007)	(0.065)	(0.004)	(0.073)				
SIC31	0.025	0.431***	-0.009	0.517***	0.420	-0.009	0.504	0.92
(Furniture)	(0.055)	(0.108)	(0.051)	(0.071)				
SIC32	0.022	0.244***	-0.001	0.735***	0.239	-0.001	0.718	0.96
(Other Manufacturing)	(0.016)	(0.050)	(0.010)	(0.068)				
SIC33	0.062***	0.593***	0.025***	0.286***	0.556	0.023	0.268	0.85
(Repair and Installation)	(0.008)	(0.051)	(0.006)	(0.054)				

Notes: Number of observations are reported in Table AII 6 in Appendix II, where there are 148,962 and 112,503 observations for manufacturing and ICT, respectively. η refers to industry deflated revenue elasticity. $(\eta/\eta-1)\beta_m$, $(\eta/\eta-1)\beta_k$, and $(\eta/\eta-1)\beta_l$ refer to revenue elasticity of materials, capital, and materials. β_m, β_k, and β_l refer to implied output elasticity of capital. RS refers to return to scale (calculated as the sum of the output elasticities).

First, Table 1a shows the estimated industry revenue (column 1), revenue (columns 2-4), and implied output elasticities (columns 5-7) from our revenue production function for the entire manufacturing sector. Table 1b then shows the results for the ICT sector.[22] Both tables show that the estimated revenue elasticities with respect to materials and labour exhibit substantially more variation than those with respect to capital input. We also find that firms within each SIC2 sector are generally close to constant returns to scale (see column 8). We formally test a constant returns to scale restriction in the robustness section below.

[22] See Appendix II Tables II 1a to II 1d for the estimated revenue, implied output elasticities, and industry revenue elasticity from our revenue production function for the electricity, wholesale trade and retails, transportation, and finance sectors, respectively.

Table 1b. Information and Communication Implied CRS (firm-level average)

	$1/\eta$	$(\eta/\eta-1)\beta_m$	$(\eta/\eta-1)\beta_k$	$(\eta/\eta-1)\beta_l$	β_m	β_k	β_l	RS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SIC58	0.081***	0.310***	0.0004	0.557***	0.284	0.0004	0.512	0.80
(Publishing Activities)	(0.007)	(0.058)	(0.004)	(0.067)				
SIC59	0.008	0.042	0.060***	0.728***	0.041	0.060	0.722	0.82
(Motion Picture)	(0.012)	(0.042)	(0.007)	(0.069)				
SIC60	0.027	0.029	0.035	0.550***	0.028	0.034	0.535	0.60
(Programming & Broadcasting)	(0.066)	(0.157)	(0.048)	(0.217)				
SIC61	0.072***	0.357***	0.022***	0.565***	0.332	0.020	0.524	0.88
(Telecommunications)	(0.003)	(0.027)	(0.002)	(0.026)				
SIC62	0.088***	0.431***	0.018***	0.406***	0.393	0.016	0.369	0.78
(Computer Programming)	(0.005)	(0.043)	(0.004)	(0.047)				
SIC63	0.064***	0.207***	0.026***	0.590***	0.193	0.024	0.552	0.77
(Information Service)	(0.005)	(0.023)	(0.011)	(0.037)				

Notes: Number of observations are reported in Table AII 6 in Appendix II, where there are 148,962 and 112,503 observations for manufacturing and ICT, respectively. η refers to industry deflated revenue elasticity. $(\eta/\eta-1)\beta_m$, $(\eta/\eta-1)\beta_k$, and $(\eta/\eta-1)\beta_l$ refer to revenue elasticity of materials, capital, and materials. β_m, β_k, and β_l refer to implied output elasticity of capital. RS refers to return to scale.

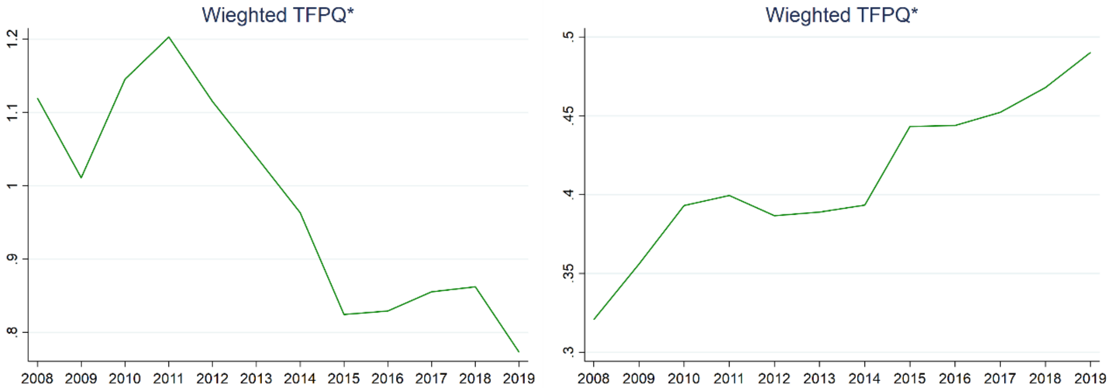


Figure 1. Revenue weighted TFPQ* Levels Overtime – Manufacturing (left) and ICT (right)

Notes: This graph reports the TFPQ* over the period through 2008-2019.

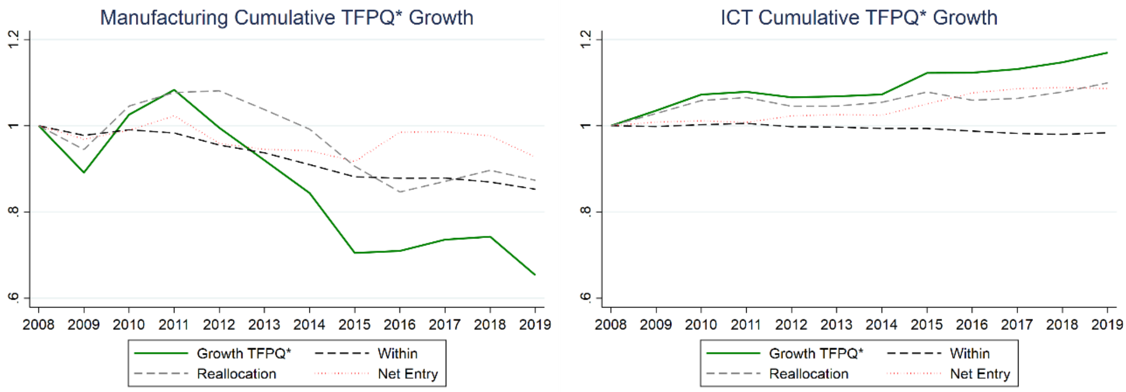


Figure 2. Revenue Weighted Cumulated TFPQ* Growth over time

Notes: The growth rate is based on revenue weighted firm-level average growth rate (i.e., sum across all firms through each year). $x_t = \sum_i \mathrm{x}_{it} S_{it}$, where S_{it} is the firm-level revenue weight and x_{it} is the firm-level TFPQ*. The growth rate of x_t is then Δx_t (log difference). The decomposition is then carried out by using $\Delta x_t = \sum_i \Delta x_{it} S_{it-1} + \sum_i \tilde{\mathrm{x}}_{i,t-1} \Delta S_{it} + \sum_i \Delta \mathrm{x}_{it} \Delta S_{it} + \sum_{i \in Entry} \tilde{\mathrm{x}}_{it} S_{it} - \sum_{i \in Exit} \tilde{\mathrm{x}}_{i,t-1} S_{i,t-1}$. We set year 2008 as 1 and adjust the index over time based on the appropriate growth rate.

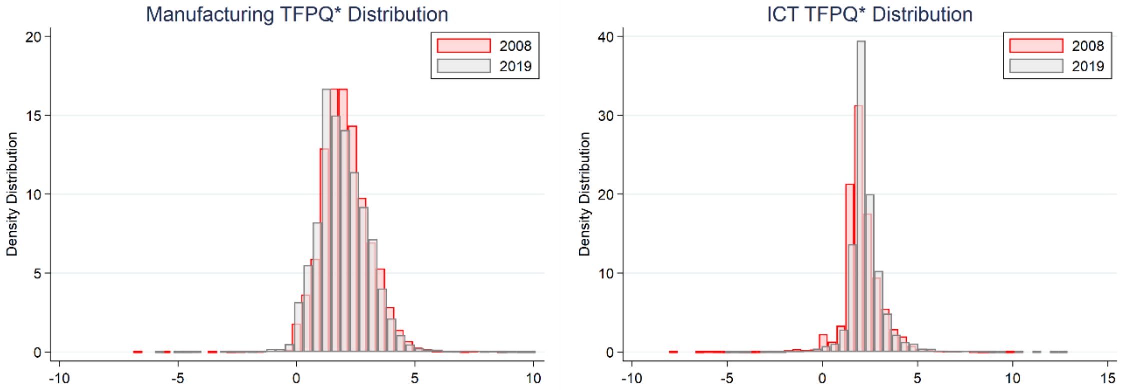


Figure 3. The Shift of Overall TFPQ* Distribution in 2008 and 2019

Notes: The x-axis represents here the TFPQ* (logs).

With estimates of firm-level revenue elasticities in hand, we can now look at the underlying trends in TFPQ*.[23] Focusing on the levels (aggregated with revenue-weights), Figure 1 reveals the evolution of the two sectoral TFP measures over time. They show divergent patterns. In manufacturing (Figure 1 left) the trend through the period is downwards, although after flatlining during the period 2015-2018, there was a jump in TFPQ* in 2019. For ICT (Figure 1 right) there is an upward trend from 2008 onwards until 2019. The quality-adjusted TFP shown here is very similar to the revenue-based TFPR (see, for instance, Figures AI 5 and 6 in Appendix I). This is consistent with Jacob and Mion (2022), who suggest that the weak productivity performance of UK firms post-recession is due to decreasing quantity TFP driving down revenue TFP.

We next look at the evolution of the sub-components of the TFPQ* index implied by our growth decomposition. This decomposition takes into account firms' entry and exit, as well as reallocations between existing firms. Figure 2 presents the trajectory over time for manufacturing and information and communication industries, respectively. For manufacturing, the striking feature of the decomposition is the consistent decline in the implied measure of within-industry TFPQ* over the period. The effects of negative growth in within-industry TFPQ* were further reinforced by adverse reallocation effects toward less productive firms. For ICT, we observe a (small) fall in within-industry TFPQ*, though the adverse movements in within-industry growth were more than offset by positive reallocation effects.

To gain additional insight into the evolution of the entire distribution, we plot the density distribution of the unweighted TFP measures for 2008 and 2019 in Figure 3 for

[23] We find that quantity (TFPQ*) and revenue-based TFP^{rr} estimates in manufacturing are similar, with TFPQ* being higher than the TFP^{rr}. See Figures AI 3 and 4 in Appendix I for more details.

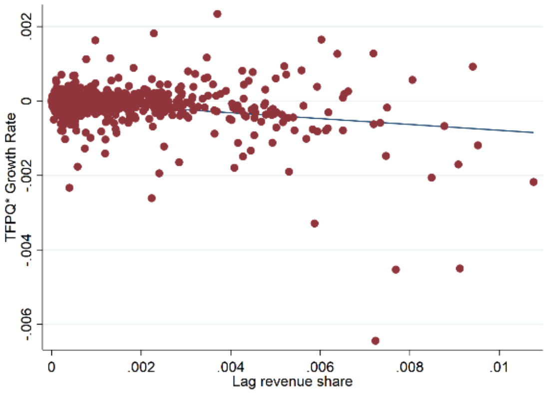


Figure 4a. TFP Growth (within) vs Lag Revenue Share - Manufacturing

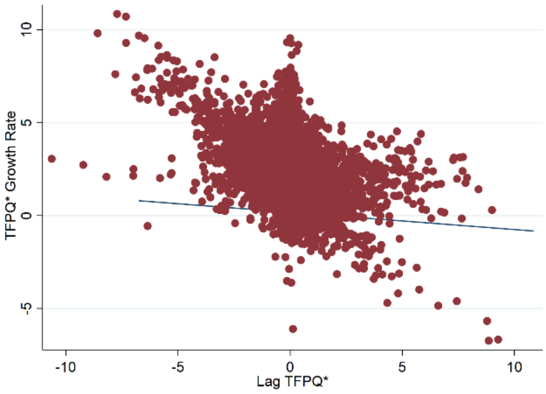


Figure 4b. TFP Growth (within) vs LagTFP - Manufacturing

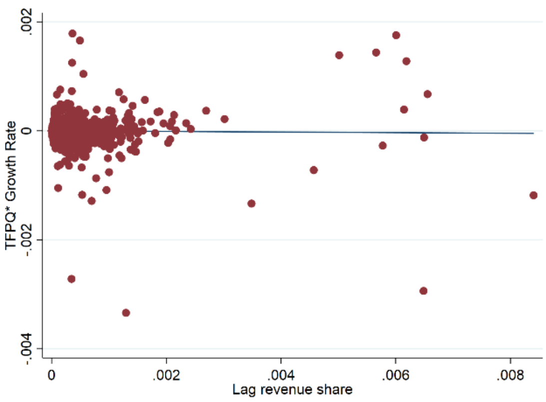


Figure 4c. TFP Growth (within) vs Lag Revenue Share – ICT

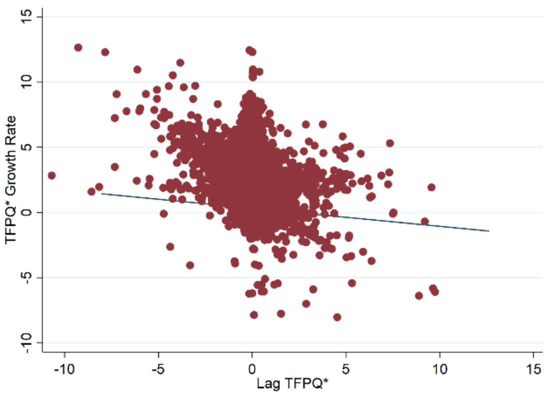


Figure 4d. TFP Growth (within) vs LagTFP – ICT

manufacturing (left) and ICT (right). We find that there is a shift towards the left in the TFP distributions in 2019 (gray) compared to 2008 (red) in manufacturing, but there is a shift toward the right in ICT. The divergent patterns (in both the shape of the distribution and the direction of the shift) point to the need to consider the dynamics of the two sectors separately, although we find here a decline in the 'within' component of TFP in both cases, and although both contribute substantially to the overall productivity slowdown at the more aggregated sector level.

To explore further the evolution of the within term of the cumulative TFP growth shown in manufacturing and ICT, we further decompose in Figure 4 the first (within-industry) element of our growth decomposition. Note that this element is the sum of the products of the firm-level TFPQ* growth rate and the firm's lagged revenue share. The consistent decline in the within-industry TFPQ* suggests that a preponderance of firms experienced declining TFPQ*.

Figure 4 shows a scatter plot of firm-level growth rates and lagged revenue shares, as well as the firm-level growth rates and lagged TFPQ*. For manufacturing (Figures 4a and 4b), we see as expected that a significant majority of firms experienced annual declines in TFPQ* growth; we see some weak evidence that larger firms, in terms of their revenue shares (Figure 4a) and TFPQ* (Figure 4b), tended to experience larger declines. For ICT (Figures 4c and 4d), we again see that a significant number of firms experienced annual declines in TFPQ*, but there does not appear to be any relationship between the size of the firms and the extent of the declines. Although not part of the decomposition, the second panel (right) in each case provides further insight into the factors driving relative firm performance by plotting the relationship between annual firm-level TFPQ* growth and its lagged level. Interestingly, we see evidence of within-industry convergence in both of the industries, with higher TFPQ* firms experiencing slower productivity growth, indicating some degree of catch-up by weaker firms.

6. Robustness checks

6.1 Constant Return to Scales

While the estimation method used in Section 5 performs well on our data in terms of recovering generally sensible estimates of the relevant elasticities, we confront a problem of low implied elasticities for capital that is common in literature (Klette and Griliches, 1996; Forlani et al., 2022). As a robustness check, we therefore test for the robustness of

Table 2a. Manufacturing – Testing for CRS

	$1/\eta$ (1)	$(\eta/\eta-1)\beta_m$ (2)	$(\eta/\eta-1)\beta_k$ (3)	1-$\bar{\beta}$=0 (4)	β_m (5)	β_k (6)	β_l (7)
SIC10	0.146***	0.527***	0.008***	-0.054	0.450	0.007	0.543
(Food Products)	(0.026)	(0.041)	(0.002)	(0.030)			
SIC11	0.088***	0.472***	0.014	0.014	0.430	0.013	0.557
(Beverages)	(0.025)	(0.055)	(0.009)	(0.035)			
SIC13	0.091***	0.302**	0.032	0.084	0.274	0.029	0.697
(Textiles)	(0.029)	(0.156)	(0.021)	(0.056)			
SIC16	0.089***	0.325***	-0.024	-0.054	0.296	-0.021	0.725
(Wood Products)	(0.019)	(0.077)	(0.038)	(0.062)			
SIC17	0.079***	0.094*	0.029***	0.099***	0.087	0.027	0.886
(Paper Products)	(0.019)	(0.054)	(0.011)	(0.027)			
SIC18	0.072***	0.174***	0.023***	-0.004	0.161	0.022	0.817
(Printing & Reproduction)	(0.013)	(0.057)	(0.006)	(0.026)			
SIC20	0.197***	0.572***	0.004	-0.105***	0.459	0.003	0.538
(Chemicals)	(0.032)	(0.075)	(0.006)	(0.026)			
SIC22	0.035***	0.724***	-0.007	0.075***	0.698	-0.006	0.308
(Rubber & Plastic)	(0.008)	(0.093)	(0.005)	(0.015)			
SIC23	0.077***	0.514***	-0.006	0.059***	0.474	-0.005	0.531
(Non-Metallic Mineral)	(0.006)	(0.032)	(0.004)	(0.008)			
SIC24	0.084**	0.449***	0.0007	-0.021	0.411	0.0007	0.588
(Basic Metals)	(0.039)	(0.093)	(0.007)	(0.031)			
SIC25	0.103***	0.350***	0.006	0.044	0.313	0.005	0.682
(Fabricated Metal)	(0.013)	(0.084)	(0.006)	(0.028)			
SIC26	0.156***	0.240***	-0.006	-0.098	0.203	-0.005	0.802
(Comp., Elec. & Optical)	(0.041)	(0.070)	(0.009)	(0.068)			
SIC27	0.129***	0.430***	-0.0003	-0.045	0.374	-0.0003	0.626
(Electrical Equipment)	(0.029)	(0.077)	(0.007)	(0.036)			
SIC28	0.111***	0.288***	0.0007	0.026	0.256	0.0006	0.743
(Machinery and Eqp. n.e.c.)	(0.016)	(0.062)	(0.004)	(0.016)			
SIC29	0.048***	0.496***	0.001	0.044**	0.472	0.001	0.527
(Motor Vehicles)	(0.013)	(0.064)	(0.004)	(0.019)			
SIC30	0.031***	0.469	-0.002	0.080***	0.452	-0.001	0.549
(Other Transport Eqp.)	(0.010)	(0.058)	(0.005)	(0.014)			
SIC31	0.046***	0.462***	-0.009	0.015	0.440	-0.009	0.569
(Furniture)	(0.013)	(0.075)	(0.017)	(0.020)			
SIC32	0.039***	0.196***	-0.008	0.021	0.188	-0.006	0.818
(Other Manufacturing)	(0.015)	(0.039)	(0.013)	(0.027)			
SIC33	0.076***	0.621***	0.043***	0.039***	0.573	0.039	0.388
(Repair and Installation)	(0.008)	(0.045)	(0.009)	(0.016)			

Notes: Number of observations are reported in Table AII 6 in Appendix II. η refers to industry deflated revenue elasticity. $(\eta/\eta-1)\beta_m$ and $(\eta/\eta-1)\beta_k$ refer to revenue elasticity of materials, capital, and materials. β_m, β_k, and β_l refer to implied output elasticity of capital. Wood products include wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials. Comp., Elec. & Optical refers to manufacture of computer, electronic and optical products. Machinery and Eqp. n.e.c. refers to manufacture of machinery and equipment n.e.c. Motor vehicles refers to manufacture of motor vehicles, trailers and semi-trailers. Repair and installation refers to repair and installation of machinery and equipment. Robust standard errors are provided in parentheses.

the CRS assumption. We start with our baseline firm revenue function: $r_{it} - p_{Zt} = \frac{1}{\eta}(r_{Zt} - p_{Zt}) + \frac{(\eta-1)\beta_l}{\eta} l_{it} + \frac{(\eta-1)\beta_k}{\eta} k_{it} + \frac{(\eta-1)\beta_m}{\eta} m_{it} + \frac{\eta-1}{\eta}(\lambda_{it} + \omega_{it})$, (21)

We denote the returns to scale as $\bar{\beta}$, such that : $\beta_l + \beta_k + \beta_m = \bar{\beta}$, hence $\beta_l = \bar{\beta} - \beta_k - \beta_m$. We have constant returns to scale (CRS) when $\bar{\beta} = 1$. We now note that we can write the coefficient on the *labour input variable* as:

$$\frac{(\eta-1)\beta_l}{\eta} = \frac{(\eta-1)}{\eta}\left(1 - (1-\bar{\beta}) - \beta_k - \beta_m\right) = 1 - \frac{1}{\eta} - \frac{(\eta-1)}{\eta}(1-\bar{\beta}) - \frac{(\eta-1)}{\eta}\beta_k - \frac{(\eta-1)}{\eta}\beta_m. \quad (22)$$

Table 2b. Information and Communication – Testing for CRS

	$1/\eta$ (1)	$(\eta/\eta-1)\beta_m$ (2)	$(\eta/\eta-1)\beta_k$ (3)	1-$\bar{\beta}$=0 (4)	β_m (5)	β_k (6)	β_l (7)
SIC58	0.105***	0.307***	0.006*	0.014	0.275	0.006	0.719
(Publishing Activities)	(0.011)	(0.047)	(0.003)	(0.011)			
SIC59	0.044***	0.172***	0.074***	-0.016	0.164	0.070	0.766
(Motion Picture)	(0.010)	(0.060)	(0.009)	(0.019)			
SIC60	0.101***	0.090**	0.062***	-0.147***	0.081	0.055	0.864
(Programming & Broadcasting)	(0.029)	(0.044)	(0.017)	(0.043)			
SIC61	0.089***	0.372***	0.027***	0.024***	0.338	0.025	0.637
(Telecommunications)	(0.004)	(0.027)	(0.002)	(0.003)			
SIC62	0.119***	0.419***	0.017***	-0.042***	0.369	0.015	0.616
(Computer Programming)	(0.006)	(0.045)	(0.004)	(0.016)			
SIC63	0.079***	0.237***	0.029***	0.002	0.218	0.026	0.756
(Information Service)	(0.006)	(0.023)	(0.006)	(0.012)			

Notes: Number of observations are reported in Table AII 6 in Appendix II. η refers to industry deflated revenue elasticity. $(\eta/\eta-1)\beta_m$, $(\eta/\eta-1)\beta_k$, and $(\eta/\eta-1)\beta_l$ refer to revenue elasticity of materials, capital, and materials. β_m, β_k, and β_l refer to implied output elasticity of capital. Motion picture refers to Motion picture, video and television programme production, sound recording and music publishing activities. Computer programming includes computer programming, consultancy and related activities. Robust standard errors are provided in parentheses.

We can therefore distribute the labour term in the firm revenue function to yield a re-parameterized revenue function:

$$r_{it} - p_{Zt} - l_{it} = \frac{1}{\eta}(r_{Zt} - p_{Zt} - l_{it}) - \frac{(\eta-1)}{\eta}\left(1-\bar{\beta}\right)l_{it} + \frac{(\eta-1)\beta_k}{\eta}(k_{it} - l_{it}) + \frac{(\eta-1)\beta_m}{\eta}(m_{it} - l_{it}) + \frac{\eta-1}{\eta}(\lambda_{it} + \omega_{it}). \qquad (23)$$

Making the assumption that the elasticity of substitution is strictly greater than 1, a test for CRS is then that estimated coefficient on the labour variable is not significantly different from zero (i.e., we can't reject the null that $1-\bar{\beta}=0$). This test is performed as a standard t-test on the significance of coefficient on the labour variable. To impose CRS, we then estimate the restricted revenue function:

$$r_{it} - p_{Zt} - l_{it} = \frac{1}{\eta}(r_{Zt} - p_{Zt} - l_{it}) + \frac{(\eta-1)\beta_k}{\eta}(k_{it} - l_{it}) + \frac{(\eta-1)\beta_m}{\eta}(m_{it} - l_{it}) + \frac{\eta-1}{\eta}(\lambda_{it} + \omega_{it}). \qquad (24)$$

Tables 2a and 2b provide results for the estimation of equation (24) for manufacturing and ICT.[24] In Column (4), the table also contains the estimate of the coefficient on the labour variable in equation (23), which we use to test the CRS restriction. Most but not every SIC2 sector shows evidence consistent with the CRS restriction. The exceptions are pulp, paper and paper products (SIC17), chemical and chemical products (SIC20), rubber and plastic products (SIC22), other non-metallic mineral products (SIC23), motor vehicles, trailers and semi-trailers (SIC29), other

[24] For other sectors, see Appendix II Table AII 2a to 2d.

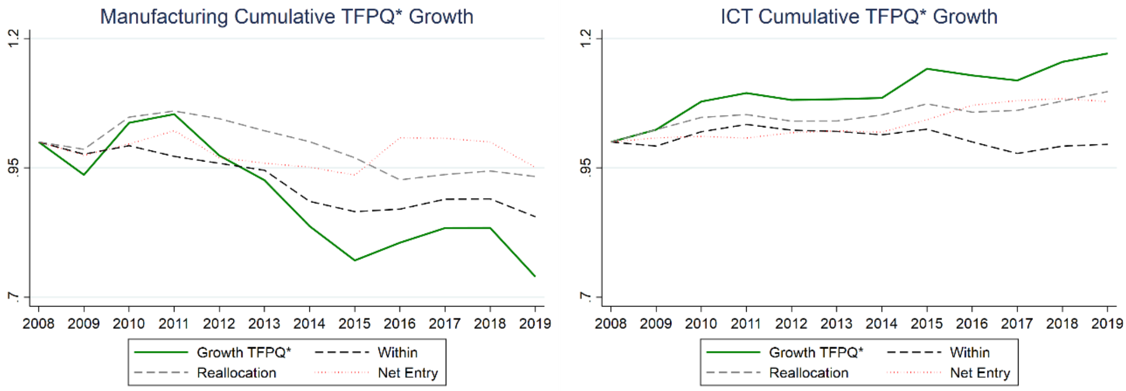


Figure 5. Revenue Weighted Cumulated TFPQ* Growth Overtime

Notes: The growth rate is based on revenue weighted firm-level average growth rate (i.e., sum across all firms through each year). $x_t = \sum_i x_{it} S_{it}$, where S_{it} is the firm-level revenue weight and x_{it} is the firm-level TFPQ*. The growth rate of x_t is then Δx_t (log difference). The decomposition is then carried out by using $\Delta x_t = \sum_i \Delta x_{it} S_{it-1} + \sum_i \tilde{x}_{i,t-1} \Delta S_{it} + \sum_i \Delta x_{it} \Delta S_{it} + \sum_{i \in Entry} \tilde{x}_{it} S_{it} - \sum_{i \in Exit} \tilde{x}_{i,t-1} S_{i,t-1}$. We set year 2008 as 1 and then add back each change onwards.

transport equipment (SIC30), and repair and installation of machinery and equipment (SIC33) for manufacturing, and programming and broadcasting activities (SIC60), telecommunications (SIC61), and computer programming, consultancy and related activities (SIC62) for information and communication. To allow comparisons with our baseline results, Figure 5 presents the cumulative growth pattern for each industry.[25] The TFPQ* are broadly similar, although we see somewhat stronger within-firm performance for ICT, with within-firm TFPQ* largely flat for the period taken as a whole. Additionally, we find a similar pattern in Tables AII 3a and 3b (in Appendix II) when the CRS is imposed by setting capital input coefficient equal to zero in the appropriately restricted specification.

6.2 Robustness to Allowing for a Fixed Component in Labour Costs

In estimating the revenue elasticities for TFPQ*, we have assumed in our baseline model that all inputs enter as variable factors of production (albeit subject to adjustment costs) in the production function. In explaining phenomena such as the declining labour share of income (e.g., Autor et al., 2020) and the growing importance of intangible capital (e.g., Goodridge, Haskel, and Wallis, 2013, 2018), recent literature has emphasised the importance of fixed factors and associated economies of scale. If a significant component of any factor has the characteristic of a fixed rather than a variable input, this could

[25] Jacob and Mion (2022) and Harris and Moffat (2017) estimate revenue per worker production functions to obtain input parameters and firm-level TFP. They also find that manufacturing firms experienced significant drops in the periods 2008-2009 and 2011-2012, respectively.

Table 3a. Manufacturing Output Elasticity Estimates – Allowing for a Fixed Component

	$1/\eta$ (1)	$(\eta/\eta-1)\beta_m$ (2)	$(\eta/\eta-1)\beta_k$ (3)	$(\eta/\eta-1)\beta_l$ (4)	β_m (5)	β_k (6)	β_l (7)	RS (8)
SIC10	0.117***	0.635***	0.002	0.021***	0.561	0.001	0.018	0.58
(Food Products)	(0.014)	(0.043)	(0.002)	(0.008)				
SIC11	0.063*	0.746***	-0.003	0.029***	0.699	-0.003	0.027	0.72
(Beverages)	(0.041)	(0.070)	(0.011)	(0.006)				
SIC13	0.096***	0.597***	0.009	0.029**	0.540	0.008	0.163	0.71
(Textiles)	(0.035)	(0.145)	(0.050)	(0.016)				
SIC16	0.085***	0.548***	-0.002	0.115**	0.500	-0.002	0.105	0.60
(Wood Products)	(0.030)	(0.161)	(0.122)	(0.063)				
SIC17	0.131***	0.376***	0.018***	0.052***	0.327	0.015	0.050	0.39
(Paper Products)	(0.024)	(0.084)	(0.007)	(0.013)				
SIC18	0.067***	0.293***	-0.023*	0.420***	0.273	-0.022	0.392	0.64
(Printing & Reproduction)	(0.016)	(0.060)	(0.012)	(0.041)				
SIC20	0.139***	0.529***	-0.006	0.130***	0.455	-0.055	0.112	0.51
(Chemicals)	(0.019)	(0.074)	(0.005)	(0.032)				
SIC22	0.028***	0.942***	-0.004	0.073***	0.915	-0.003	0.071	0.98
(Rubber & Plastic)	(0.009)	(0.038)	(0.005)	(0.032)				
SIC23	0.046***	0.799***	0.011***	0.183***	0.762	0.010	0.175	0.95
(Non-Metallic Mineral)	(0.005)	(0.020)	(0.005)	(0.012)				
SIC24	0.091***	0.727***	0.007	-0.016	0.660	0.006	-0.015	0.65
(Basic Metals)	(0.035)	(0.103)	(0.007)	(0.027)				
SIC25	0.106***	0.611***	0.004	0.224***	0.546	0.004	0.200	0.75
(Fabricated Metal)	(0.013)	(0.060)	(0.006)	(0.041)				
SIC26	0.122***	0.495***	-0.004	0.155***	0.434	-0.004	0.136	0.57
(Comp., Elec. & Optical)	(0.021)	(0.072)	(0.010)	(0.039)				
SIC27	0.130***	0.449***	0.020***	0.237***	0.390	0.017	0.206	0.61
(Electrical Equipment)	(0.023)	(0.070)	(0.007)	(0.048)				
SIC28	0.132***	0.438***	-0.0007	0.312***	0.380	-0.0006	0.271	0.65
(Machinery and Eqp. n.e.c.)	(0.020)	(0.078)	(0.005)	(0.058)				
SIC29	0.048***	0.780***	-0.008	0.026	0.742	-0.007	0.025	0.76
(Motor Vehicles)	(0.015)	(0.060)	(0.006)	(0.020)				
SIC30	0.083***	0.744***	0.009	0.189**	0.681	0.009	0.173	0.86
(Other Transport Eqp.)	(0.012)	(0.040)	(0.007)	(0.024)				
SIC31	0.016	0.718***	-0.020	0.174	0.706	-0.020	0.171	0.86
(Furniture)	(0.124)	(0.094)	(0.089)	(0.140)				
SIC32	0.018	0.648***	-0.008	0.251***	0.636	-0.008	0.247	0.88
(Other Manufacturing)	(0.017)	(0.060)	(0.009)	(0.037)				
SIC33	0.094***	0.774***	0.016***	0.072***	0.701	0.014	0.065	0.78
(Repair and Installation)	(0.009)	(0.030)	(0.007)	(0.016)				

Notes: Number of observations are reported in Table AII 6 in Appendix II. η refers to industry deflated revenue elasticity. $(\eta/\eta-1)\beta_m$, $(\eta/\eta-1)\beta_k$ and $(\eta/\eta-1)\beta_l$ refer to revenue elasticity of materials, capital, and labour. β_m, β_k, and β_l refer to implied output elasticity of materials, capital, and labour. Wood products include wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials. Comp., Elec. & Optical refers to manufacture of computer, electronic and optical products. Machinery and Eqp. n.e.c. refers to manufacture of machinery and equipment n.e.c. Motor vehicles refers to manufacture of motor vehicles, trailers and semi-trailers. Repair and installation refers to repair and installation of machinery and equipment. Robust standard errors are provided in parentheses.

significantly bias our inferences concerning the portion of revenue variability that can be explained by changing input use, thus biasing our inferences concerning the evolution of TFPQ*. For example, a fraction of a firm's labour force might be involved in product design activities, where the costs of these intangible investments do not vary with the output of the firm.

To augment our baseline model to allow for fixed input, we assume that the amount of the fixed factor is common across firms in a given industry in year *t.* We assume here that a portion of labour input is fixed. The amount of variable labour is denoted V_{it} and the amount of variable labour is denoted F_t, where $L_{it} = V_{it} + F_t$.

Table 3b. ICT Output Elasticity Estimates – Allowing for a Fixed Component

	$1/\eta$ (1)	$(\eta/\eta-1)\beta_m$ (2)	$(\eta/\eta-1)\beta_k$ (3)	$(\eta/\eta-1)\beta_l$ (4)	β_m (5)	β_k (6)	β_l (7)	RS (8)
SIC58	0.061***	0.583***	0.029***	0.167***	0.547	0.027	0.157	0.73
(Publishing Activities)	(0.008)	(0.047)	(0.008)	(0.030)				
SIC59	0.040***	0.190***	0.041***	0.348***	0.182	0.039	0.333	0.55
(Motion Picture)	(0.013)	(0.054)	(0.006)	(0.042)				
SIC60	0.069***	0.265***	0.041***	0.235***	0.247	0.038	0.218	0.50
(Programming & Broadcasting)	(0.015)	(0.057)	(0.014)	(0.064)				
SIC61	0.108***	0.676***	0.013***	0.199***	0.603	0.012	0.178	0.79
(Telecommunications)	(0.003)	(0.017)	(0.002)	(0.007)				
SIC62	0.098***	0.564***	0.020***	0.245***	0.508	0.018	0.221	0.75
(Computer Programming)	(0.006)	(0.032)	(0.005)	(0.026)				
SIC63	0.134***	0.365***	0.016	0.339***	0.315	0.014	0.293	0.62
(Information Service)	(0.006)	(0.020)	(0.010)	(0.016)				

Notes: Number of observations are reported in Table AII 6 in Appendix II. η refers to industry deflated revenue elasticity. $(\eta/\eta-1)\beta_m$, $(\eta/\eta-1)\beta_k$, and $(\eta/\eta-1)\beta_l$ refer to revenue elasticity of materials, capital, and labour. β_m, β_k, and β_l refer to implied output elasticity of materials, capital, and labour. Motion picture refers to Motion picture, video and television programme production, sound recording and music publishing activities. Computer programming includes computer programming, consultancy and related activities. Robust standard errors are provided in parentheses.

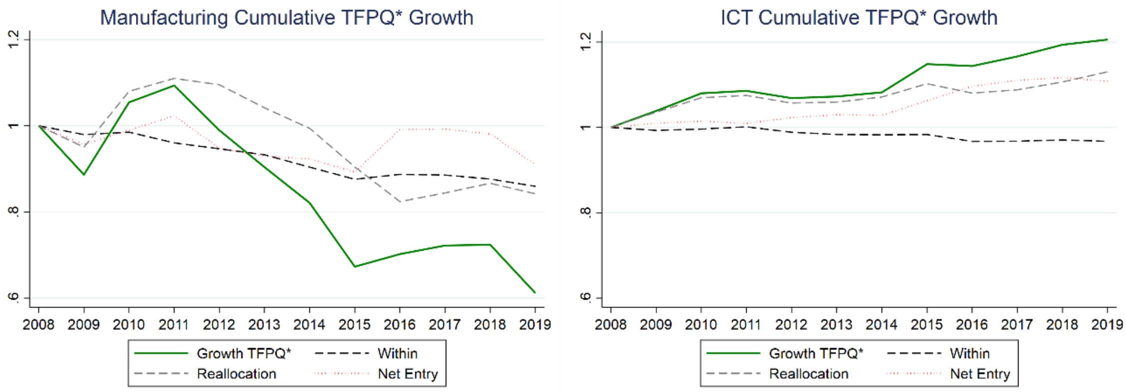


Figure 6. Revenue Weighted Cumulated TFPQ* Growth Overtime

Notes: The growth rate is based on revenue weighted firm-level average growth rate (i.e., sum across all firms through each year). $x_t = \sum_i x_{it} S_{it}$, where S_{it} is the firm-level revenue weight and x_{it} is the firm-level TFPQ*. The growth rate of x_t is then Δx_t (log difference). The decomposition is then carried out by using $\Delta x_t = \sum_i \Delta x_{it}\, S_{it-1} + \sum_i \tilde{x}_{i,t-1}\Delta S_{it} + \sum_i \Delta x_{it}\Delta S_{it} + \sum_{i\in Entry} \tilde{x}_{it} S_{it} - \sum_{i\in Exit} \tilde{x}_{i,t-1} S_{i,t-1}$. We set year 2008 as 1 and then add back each change onwards.

Under monopolistic competition and a given industry-specific elasticity of substitution, Autor et al. (2017, 2020) note that labour's share in total revenue is given by:

$$s_{it}^L = \frac{w_{it}L_i}{P_{it}Q_{it}} = \frac{w_{it}(V_{it}+F_t)}{P_{it}Q_{it}} = \frac{\beta_l}{\mu} + F_t \frac{w_{it}}{P_{it}Q_{it}}. \tag{25}$$

Thus, for a given industry in a given year, it is possible, in principle, to estimate the size of the fixed labour factor from a simple regression of the labour share of total revenue on a constant (assuming the output elasticity of labour and the mark-up are both constant) and the ratio of the wage to firm revenue. Note that we allow the average wage to be firm specific given likely differences in composition of firm labour forces, so that the average wage is calculated as the wage bill divided by employment in the firm. The fixed factor is then the coefficient on the ratio of the wage to firm revenue variable in this simple bivariate regression.

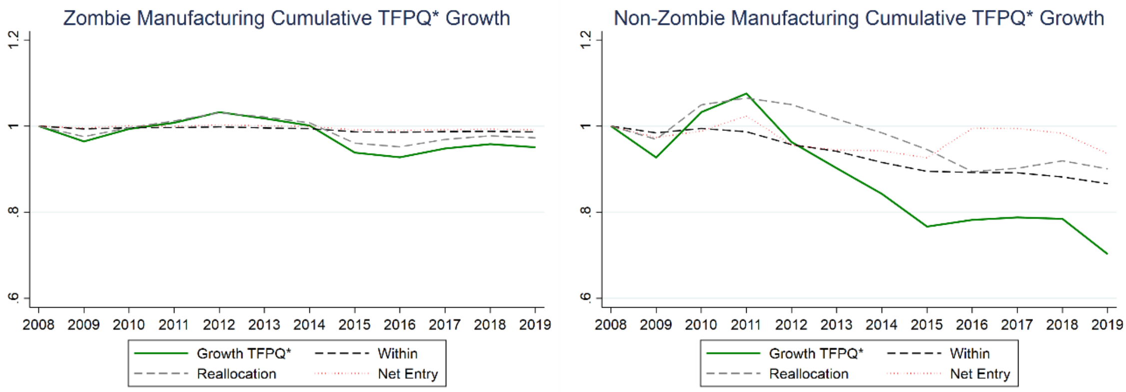
Once Eq. (25) is estimated for industry and for year, and the time-varying fixed cost identified as the coefficient on wage/revenue variable, we then subtract the estimated fixed component of labour input from the total labour input variable to obtain an estimate variable labour input. We then re-estimate our revenue function Eq. (12) based only on the estimated variable labour input and infer TFPQ* as outlined in Section 2. Tables 3a and 3b provide the results for manufacturing and ICT.[26] The results are broadly similar to our baseline, but with an estimated revenue elasticity of variable labour input lower than the estimate without adjusting for fixed costs. Figure 6 shows TFPQ* evolutions that are again broadly similar to our baseline results. Additionally, we explore imposing the constant returns to scale restriction and the allowance for fixed labour costs together. The results are provided in Appendix II Tables AII 5a to 5b and Figure AI 7 in Appendix I[27]. The results are again broadly consistent with our baseline results shown in Figure 6.

6.3 "Zombies", Domestic, and Foreign Firms

While we have conducted several checks to indicate the robustness of our results, two concerns remain. First, there is an issue with 'zombie' firms, which are heavily in debt enterprises with no capacity to repay their debt due to prolonged unprofitability. These entities behave as outliers and a question is whether our findings so far are influenced by this type of firms in our sample. We follow Carreira, Teixeira, and Nieto-Carrillo (2022) and Osterhold and Gouveia (2020), indefining a firm as "zombie" the ratio of total revenue to interest expenses over a three consecutive years period (i.e., a moving average over three years from $t-1$, t, and $t+1$) is less than two.[28] The three-year window restriction is necessary to ensure that the "zombie" status is not driven by business cycle fluctuations (McGowan, Andrews, and Millot, 2018).

[26] Appendix II Tables AII 4a to 4d again provide results for other sectors.
[27] Appendix I Figures AI 8 and 9 provide results for other industries.
[28] While the literature typically defines zombies based on an interest coverage ratio of less than one, we have observed that applying this criterion results in the identification of very few zombie firms. To ensure an adequate range of variation, we have adjusted the criterion from one to two. Nevertheless, altering this criterion does not significantly affect the results we have presented.

Panel A Manufacturing



Panel B ICT

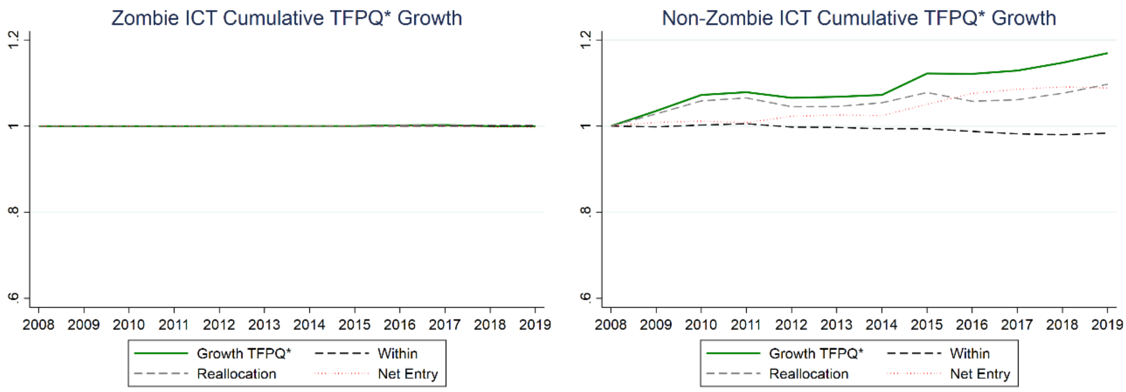


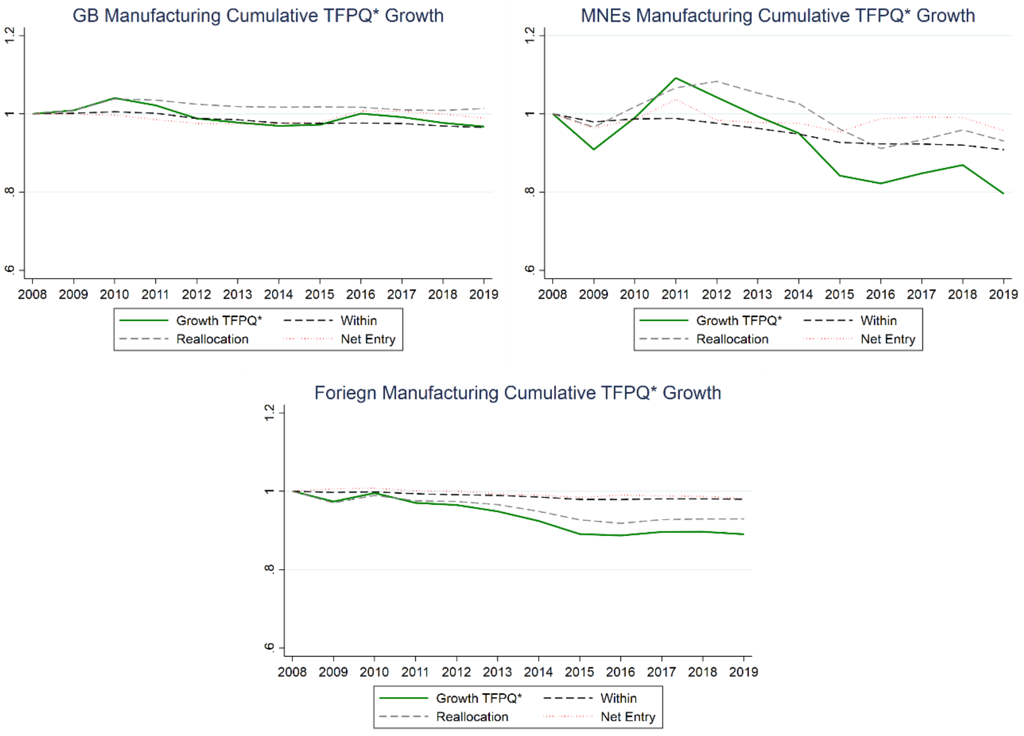
Figure 7: Zombies vs Non-Zombies in Manufacturing (Panel A) and ICT (Panel B)

Notes: For manufacturing, There are 662 zombie observations (96 firms) and 159,652 non-zombie observations (56,874 firms) over the period 2008-2019. For ICT, there are 591 zombie observations (82 firms) and 111,912 for non-zombie observations (39,918 firms).

Figure 7, which presents the results for the two industries, demonstrates that our previous findings persist even after distinguishing between "zombie" and "non-zombie" firms. Regarding the ICT sector, Figure 7 Panel B confirms that the growth of TFPQ* is primarily driven by "non-zombie" firms. A similar results is true in Figure 7 Panel A for the manufacturing sector.

Secondly, there is a rich body of existing research that highlights productivity differences between foreign-owned and domestic-owned firms. For instance, Bertrand and Zitouna (2008) for France, Chen (2011) for the United States, Griffith (1999), Conyon, Girma, Thompson, and Wright (2002) and Girma and Görg (2007) for the UK, Arnold and Javorcik (2009) for Indonesia, and Djankov and Hoekman (2000) for Czech Republic found that foreign acquisitions positively affect the productivity of the target firms. Harris and Robinson (2002) also observed foreign-owned firms to outperform domestically-owned counterparts over the period 1974–1995. However, Benfratello and Sembenelli (2006) for Italy, Almeida (2007) for Portugal, and Wang and Wang (2015) for

Panel A Manufacturing



Panel B ICT

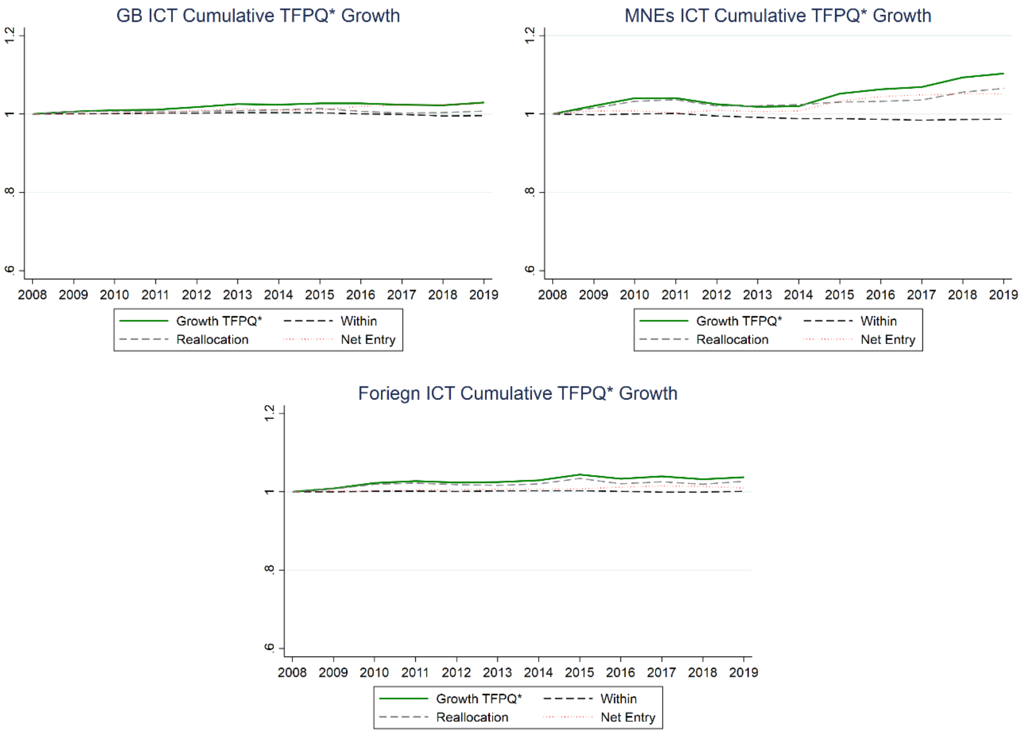


Figure 8. GB vs MNEs vs Foreign in Manufacturing (Panel A) and ICT (Panel B)

Notes: There are 160,314 observations, in which 50,063 observations for GB firms (15,687 firms), 15,270 observations for acquired (2,137 firms), and 94,981 observations for MNEs (39,146 firms). For ICT, there are 112,503 observations, in which 52,298 observations for GB firms (11,595 firms), 4,801 observations for acquired (710 firms), and 55,404 observations for MNEs (27,695 firms).

China found that foreign acquisitions do not improve the performance of the target firms. Bircan (2019) examines foreign acquisitions in Turkey and found that foreign acquisition raises target firms' physical productivity but lowers price and constant markup.

Since the dataset provide information on firms' foreign ownership status[29] and their foreign origin, we can identify three categories of firms: (1) "Foreign Acquired" (labelled as "Foreign") refers to firms initially domestically owned (i.e., GB firms)[30] but later acquired by foreign firms; (2) "Domestically Owned" (labelled as "GB") refers to firms that have never been acquired by any foreign firm; and (3) "Foreign MNEs" (labelled as "MNEs") refers to firms shown as foreign-owned from their first entry year and continuously owned by foreign firms. Figure 8 presents the results, showing productivity differences among these different types of firms and in both industries. In particular, Figure 8 Panel A reveals that domestic-owned firms in manufacturing, perform relatively well compared to others, suggesting that the slow growth of TFPQ* is mainly driven by MNEs and foreign-acquired firms. In the ICT sector, as shown in Figure 8 Panel B, we find that all firms perform equally well during the period 2008-2019.

7. Conclusion

To gain a better understanding of the productivity slowdown in the UK over the last two decades, it is essential to have first consistent and unbiased TFP measures.. In this paper, we use data on output revenue and input expenditures to develop new estimation framework that derives quality-adjusted TFP (TFPQ*). The proposed TFP measure already accounts for increases in TFP due to quality improvement, so any observed difference over time is attributed to changes in physical TFP. Using functional form assumptions, the derivation of TFPQ is obtained through requires are the estimation of the elasticity of substitution without using information on unit price data, which are rarely available in firm level data. Adapting a method pioneered Klette and Griliches (1996), we show that, under our assumptions, an estimate of this elasticity is recoverable from the estimated coefficient on a deflated industry revenue variable in the firm-level revenue function. This is a significant element in our paper that enhances its appeal for potential applications in the future. We address endogeneity in the econometric

[29] The ABS dataset defines a firm as foreign-owned if more than 50% of its stock or equity is ultimately owned by a foreign investor.

[30] The GB firms exclude all firms in Northern Ireland since the Annual Business Survey does not cover firms in Northern Ireland.

estimation of the firm-level revenue function using the instrumental variable-based Blundell-Bond System GMM estimator, which is specifically designed for estimating production functions.

The evolutions of firm- and industry-level TFPQ* are striking, and vary substantially between Manufacturing and ICT. For manufacturing, we find that annual firm-level TFPQ* fell for a majority of firms, leading to a more than 10 percent decline in the within-firm measure of TFPQ* at the industry level over the sample period. Adverse reallocation effects, including allowance for firm entry and exit, reinforced these within-firm declines. For ICT, we find a small fall in within-firm TFPQ*, although this was offset by beneficial reallocation effects.

The within-firm declines are puzzling; we conjecture that they reflect product-quality related effects – possibly related to international competition – rather than outright technological regression. A limitation of the present study is that the modelling framework assumes a closed economy. While the data does include revenues from the exports of UK firms, we do not observe the share of revenue from exports as well as the share of imports expenditure. . One plausible explanation for our within-firm TFPQ* is that UK companies may be struggling to compete in terms of quality with international counterparts. Given the importance of this finding for social welfare and prosperity, the investigation of the issue is a priority for future work.

There are other potential future extensions of our results. While the focus of this paper has been on measuring firm-level TFPQ*, the next important step is to understand the drivers of TFPQ* performance. In an ongoing work Coyle et al. (2023b), we are examining some of these drivers, such as the adoption of digital technologies and the relevance of foreign ownership – including observed changes in ownership. Although ownership status did not affect our results, both these aspects remain important for understanding the differences in the distribution of firm TFPQ* between the two sectors.

Although the present framework allows for the derivation of markups, we have not implemented this estimation in the present paper but in our ongoing work Coyle et al. (2023a). Relaxing the assumption of monopolistic competition allows for estimating time variable markups in a fashion similar to De Loecker and Warzynski (2012) methodology. The next path of future research is to explore the evolution of price markups in UK firms and their associated impact in the observed productivity slowdown of specific sectors. As productivity laggardness in the UK has a been in the spotlight of the policy making agenda, continuous research is always needed for improving our understanding on the topic.

References

Ackerberg, D.A., Caves, K. and Frazer, G., 2015. Identification properties of recent production function estimators. *Econometrica*, *83*(6), pp.2411-2451.

Adalet McGowan, M., Andrews, D. and Millot, V., 2018. The walking dead? Zombie firms and productivity performance in OECD countries. Economic Policy, 33(96), pp.685-736.

Almeida, R., 2007. The labor market effects of foreign owned firms. *Journal of international Economics*, *72*(1), pp.75-96.

Andrews, D., Criscuolo, C. and Gal, P.N., 2019. *The best versus the rest: divergence across firms during the global productivity slowdown* (No. dp1645). Centre for Economic Performance, LSE.

Arnold, J.M. and Javorcik, B.S., 2009. Gifted kids or pushy parents? Foreign direct investment and plant productivity in Indonesia. *Journal of International Economics*, *79*(1), pp.42-53.

Autor, D., Dorn, D., Katz, L.F., Patterson, C. and Van Reenen, J., 2020. The fall of the labor share and the rise of superstar firms. *The Quarterly Journal of Economics*, *135*(2), pp.645-709.

Basu, S., 2019. Are price-cost markups rising in the United States? A discussion of the evidence. *Journal of Economic Perspectives*, *33*(3), pp.3-22.

Benfratello, L. and Sembenelli, A., 2006. Foreign ownership and productivity: Is the direction of causality so obvious?. *International Journal of Industrial Organization*, *24*(4), pp.733-751.

Berry, S., Gaynor, M. and Scott Morton, F., 2019. Do increasing markups matter? lessons from empirical industrial organization. *Journal of Economic Perspectives*, *33*(3), pp.44-68.

Bertrand, O. and Zitouna, H., 2008. Domestic versus cross-border acquisitions: which impact on the target firms' performance?. *Applied economics*, *40*(17), pp.2221-2238.

Bircan, Ç., 2019. Ownership structure and productivity of multinationals. *Journal of international economics*, *116*, pp.125-143.

Blundell, R. and Bond, S., 1998. Initial conditions and moment restrictions in dynamic panel data models. *Journal of econometrics*, *87*(1), pp.115-143.

Blundell, R. and Bond, S., 2000. GMM estimation with persistent panel data: an application to production functions. *Econometric reviews*, *19*(3), pp.321-340.

Bond, S., Hashemi, A., Kaplan, G. and Zoch, P., 2021. Some unpleasant markup arithmetic: Production function elasticities and their estimation from production data. *Journal of Monetary Economics*, *121*, pp.1-14.

Brand, J., 2019. *Estimating Productivity and Markups Under Imperfect Competition*. Working paper.

Carreira, C., Teixeira, P. and Nieto-Carrillo, E., 2022. Recovery and exit of zombie firms in Portugal. *Small Business Economics*, *59*(2), pp.491-519.

Chen, W., 2011. The effect of investor origin on firm performance: Domestic and foreign direct investment in the United States. *Journal of international economics*, *83*(2), pp.219-228.

Ciapanna, E., Formai, S., Linarello, A. and Rovigatti, G., 2022. Measuring market power: macro and micro evidence from Italy. *Bank of Italy Occasional Paper*, (672).

Conyon, M.J., Girma, S., Thompson, S. and Wright, P.W., 2002. The impact of mergers and acquisitions on company employment in the United Kingdom. *European Economic Review*, *46*(1), pp.31-49.

Coyle, D., Lind, K., Nguyen, D. and Tong, M., 2022. Are digital-using UK firms more productive?. *Economic Statistics Centre of Excellence Discussion Paper*, (2022-06).

Coyle, D. and Mei, J.C., 2023. Diagnosing the UK productivity slowdown: which sectors matter and why?. *Economica*, *90*(359), pp.813-850.

Coyle, D. and McHale, J. and Bournakis, I., and Mei, J.C., 2023a. Recent Trends in Firm-Level Markups in the United Kingdom 2008-2019. *Working Paper*.

Coyle, D. and McHale, J. and Bournakis, I., and Mei, J.C., 2023b. Digital Economy and UK Productivity. *Working Paper*.

Crafts, N. and Mills, T.C., 2020. Is the UK productivity slowdown unprecedented?. *National Institute Economic Review*, *251*, pp.R47-R53.

De Loecker, J., 2011. Product differentiation, multiproduct firms, and estimating the impact of trade liberalization on productivity. *Econometrica*, *79*(5), pp.1407-1451.

De Loecker, J. and Warzynski, F., 2012. Markups and firm-level export status. American economic review, 102(6), pp.2437-71.

De Loecker, J. and Goldberg, P.K., 2014. Firm performance in a global market. Annu. Rev. Econ., 6(1), pp.201-227.

De Loecker, J., Goldberg, P.K., Khandelwal, A.K. and Pavcnik, N., 2016. Prices, markups, and trade reform. Econometrica, 84(2), pp.445-510.

De Loecker, J., Eeckhout, J. and Unger, G., 2020. The rise of market power and the macroeconomic implications. *The Quarterly Journal of Economics*, *135*(2), pp.561-644.

De Loecker, J., 2021. Comment on (Un) pleasant... by Bond et al (2020). *Journal of Monetary Economics*, *121*, pp.15-18.

De Ridder, M., Grassi, B. and Morzenti, G., 2022. *The Hitchhiker's Guide to Markup Estimation*. Centre for Economic Policy Research.

de Vries, K., Erumban, A. and van Ark, B., 2021. Productivity and the pandemic: short-term disruptions and long-term implications: The impact of the COVID-19 pandemic on productivity dynamics by industry. *International Economics and Economic Policy*, *18*(3), pp.541-570.

Djankov, S. and Hoekman, B., 2000. Foreign investment and productivity growth in Czech enterprises. *The World Bank Economic Review*, *14*(1), pp.49-64.

Forlani, E., Martin, R., Mion, G. and Muûls, M., 2022. Unraveling firms: Demand, productivity and markups heterogeneity.

Fernald, J. and Inklaar, R., 2022. The UK Productivity "Puzzle" in an International Comparative Perspective. Federal Reserve Bank of San Francisco.

Foster, L.S., Haltiwanger, J.C. and Tuttle, C., 2022. *Rising Markups or Changing Technology?* (No. w30491). National Bureau of Economic Research.

Garcia-Marin, A. and Voigtländer, N., 2019. Exporting and plant-level efficiency gains: It's in the measure. *Journal of Political Economy*, *127*(4), pp.1777-1825.

Gibbon, A.J. and Schain, J.P., 2022. Rising markups, common ownership, and technological capacities. *International Journal of Industrial Organization*, p.102900.

Girma, S. and Görg, H., 2007. Evaluating the foreign ownership wage premium using a difference-in-differences matching approach. *Journal of International Economics*, *72*(1), pp.97-112.

Goodridge, P., Haskel, J. and Wallis, G., 2013. Can intangible investment explain the UK productivity puzzle?. *National Institute Economic Review*, *224*(1), pp.R48-R58.

Goodridge, P., Haskel, J. and Wallis, G., 2018. Accounting for the UK productivity puzzle: a decomposition and predictions. *Economica*, *85*(339), pp.581-605.

Goodridge, P. and Haskel, J., 2023. Accounting for the slowdown in UK innovation and productivity. *Economica*, *90*(359), pp.780-812.

Griffith, R., 1999. Using the ARD establishment level data to look at foreign ownership and productivity in the United Kingdom. *The Economic Journal*, *109*(456), pp.416-442.

Haltiwanger, J., 1997. Measuring and analyzing aggregate fluctuations: the importance of building from microeconomic evidence. *Federal Reserve Bank of St. Louis Review*, (May), pp.55-78.

Harris, R. and Moffat, J., 2017. The UK productivity puzzle, 2008–2012: evidence using plant-level estimates of total factor productivity. *Oxford Economic Papers*, *69*(3), pp.529-549.

Kané, A., 2022. Measurement of total factor productivity: Evidence from French construction firms. *EconomiX Working Papers*, (2022-9).

Klette, T.J., 1999. Market power, scale economies and productivity: estimates from a panel of establishment data. *The Journal of Industrial Economics*, *47*(4), pp.451-476.

Klette, T.J. and Griliches, Z., 1996. The inconsistency of common scale estimators when output prices are unobserved and endogenous. *Journal of applied econometrics*, *11*(4), pp.343-361.

Jacob, N. and Mion, G., 2022. The UK's great demand and supply recession. *Oxford Bulletin of Economics and Statistics* (forthcoming).

Macedoni, L. and Weinberger, A., 2022. Quality heterogeneity and misallocation: The welfare benefits of raising your standards. *Journal of International Economics*, *134*, p.103544.

Melitz, M. and Ottaviano, G.I., 2001. *Estimating firm-level productivity in differentiated product industries*. Mimeo, Harvard University.

Nickell, S., 1981. Biases in dynamic models with fixed effects. Econometrica: Journal of the econometric society, pp.1417-1426.

Olley, S. and Pakes, A., 1992. The dynamics of productivity in the telecommunications equipment industry.

Osterhold, C. and Gouveia, A.F., 2020. Productivity, zombie firms and exit barriers in Portugal. *International Productivity Monitor*, (38), pp.29-49.

Vives (1999), *Oligopoly Pricing: Old Ideas and New Tools*, The MIT Press: Cambridge, MA.

Van Ark, B., De Vries, K. and Erumban, A., 2021. How to not miss a productivity revival once again. *National Institute Economic Review*, *255*, pp.9-24.

van Heuvelen, G.H., Bettendorf, L. and Meijerink, G., 2021. Markups in a dual labour market: The case of the Netherlands. *International Journal of Industrial Organization*, *77*, p.102762.

van Vlokhoven, H., 2022. Decomposing the Rise in Markups. *Working Paper*.

Syverson, C., 2019. Macroeconomics and market power: Context, implications, and open questions. *Journal of Economic Perspectives*, *33*(3), pp.23-43.

Sampi, J., Jooste, C. and Vostroknutova, E., 2021. Identification Properties for Estimating the Impact of Regulation on Markups and Productivity.

Wang, J. and Wang, X., 2015. Benefits of foreign ownership: Evidence from foreign direct investment in China. *Journal of International Economics*, *97*(2), pp.325-338.