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The UK's Great Demand and Supply Recession*

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Abstract

We revisit the weak productivity performance of the UK since the Great Recession by means of both a suitable theoretical framework and firm-level price and quantity data for detailed products, allowing us to measure both demand and its changes over time and distinguish between quantity total factor productivity and revenue total factor productivity. This in turn allows us to measure how changes in quantity TFP, demand and markups ultimately affected revenue TFP, as well as labour productivity, over the Great Recession. Our findings suggest that the weak productivity performance of UK firms post-recession is due to both weakening demand and decreasing quantity TFP pushing down sales, markups, revenue TFP and labour productivity.

I. Introduction

The Covid-19 pandemic has forced a number of countries to shut down large parts of their economies leaving millions of people at home and many businesses at risk of bankruptcy. Meanwhile, governments have put in place large rescue packages that will severely affect the public debt to GDP ratio, already high almost everywhere because the world has not

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yet completely recovered from the previous crisis, i.e. the 2008–09 Great Recession; a recession we have not fully understood yet. In this paper we revisit, with the help of new data and a suitable framework, the impacts of the Great Recession on output and productivity for the UK. In doing so, we provide a number of new insights that we believe could be useful to better understand how the Great Recession has affected countries other than the UK as well as to inform current discussions on the Covid-19 crisis.

Nine years after the end of the Great Recession in the UK, labour productivity has barely returned to the level it reached on the eve of the downturn at the end of 2007 (Office for National Statistics, 2018b). Output per hour worked grew just 1.8% between the start of 2008 and the end of 2017: had it grown at its 1994–2007 trend, it would have been 19.6% higher.[1] This poor performance is a puzzle. A sustained period of little to no labour productivity growth following a recession is indeed rare in the UK's historical record.[2] Furthermore, the productivity slowdown has occurred despite a buoyant labour market,[3] and the UK's experience is widely judged to have been worse than most of its EU and OECD peers.[4] Although many complementary explanations have been put forward, little attention has been paid to the role of demand and markups as well as to the crucial distinction between quantity total factor productivity (TFP-Q), i.e. the capacity to turn inputs into more physical output (number of shirts, litres of beer), and revenue total factor productivity (TFP-R), i.e. productivity calculated using (price-index deflated) revenue or value added as a measure of output and so the capacity to turn inputs into more revenue/value added.

Regarding the role of demand, the problem is that without actual data on products' prices and quantities it is not possible to measure demand and its changes over time and so assess whether, and to what extent, a fall in demand might have contributed to the UK productivity slowdown. For example, if revenues increase less than the price index one might well conjecture that the underlying unobservable quantities sold have decreased, but it would not be possible to establish whether the decrease in quantities is simply due to price changes, and firms moving along the same demand curve, or due to changes in the underlying demand curve that firms face. At the same time, the unavailability of data on products' prices and quantities does not allow to distinguish properly between quantity TFP and revenue TFP.[5]

In this paper we provide novel evidence that the poor productivity performance of UK firms post-2008 is due to both weakening demand and sluggish TFP-Q growth pushing down sales, markups and revenue TFP, as well as labour productivity. More specifically,

[1] Our period of analysis ends in 2013 and at that point, output per hour was 1.7% lower than at the end of 2007. Had it grown at its 1994–2007 trend rate, it would have been 14.4% higher.

[2] Four years after the end of the recessions that began in 1973, 1980 and 1990, labour productivity was between 5% and 15% higher than its previous peak (Grice, 2012).

[3] See, for example Bryson and Forth (2016) and Pessoa and Van Reenen (2014).

[4] See, for example OECD (2018) and Office for National Statistics (2018a). There is evidence that the productivity slowdown in the US and major European economies pre-dates the financial crisis (Cette, Fernald, and Mojon, 2016) but the UK experience, as documented by Office for National Statistics (2018b), shows a marked slowdown of the productivity growth trend in the recovery from the 2008-09 recession.

[5] Both macro and micro productivity studies use price indices to deflate nominal sales, or value added, in order to measure output and its changes over time. However, nominal price changes do not correspond to price index changes and so standard price-index deflated nominal values still contain a price measure and that is why we label productivity measures obtained with this approach as revenue-TFP measures.

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in the first part of our analysis we focus on manufacturing firms and use information on firm-level prices and quantities for detailed products, as well as inputs over the period 2003–13, to measure firm-level quantity TFP by building upon the frameworks developed in De Loecker *et al.* (2016) and Forlani *et al.* (2016).[6] This allows us to further quantify firm-level markups, as well as firm-level demand and its changes over time and, while aggregating the information at the manufacturing industry-level, compare the evolution of TFP-Q, markups and demand before and after 2008. Finally, we exploit two exact decompositions for TFP-R and labour productivity to show how changes in TFP-Q, markups and demand have affected the two productivity measures. Our results indicate that the poor productivity outcomes of UK manufacturing firms after 2008 are due to weakening demand and sluggish TFP-Q growth. More specifically, the decline in TFP-Q is the main reason behind the decline in revenue TFP while the slowing of demand is the key factor causing the decline in labour productivity.

In the second part of our analysis, we instead consider services and estimate a restricted version of the model due to the absence of reliable and meaningful information on prices and quantities. In doing so we find, for those measures that are common to both the full and restricted versions of the model, very similar patterns to those obtained for manufacturing. These findings, along with the absence of noticeable differences in capital stock investment patterns between manufacturing and services industries, lead us to conjecture that both demand and TFP-Q are also responsible for the poor revenue TFP and labour productivity performance of UK service industries.

We believe that our results are important for at least two reasons. First, they are informative about the long-term impacts of the Great Recession. A fall in quantity TFP, due for example to slower technical progress, represents a permanent loss of productive potential with substantial long-term implications for the economy. By contrast a demand downturn, due for example to a general climate of uncertainty, could have less permanent consequences. Second, they are informative about the policies that could more effectively address the weak growth of labour productivity and revenue TFP post-2008. In particular, our findings suggest that government policies should more prominently act towards boosting demand for firms rather than focusing only on productivity. In this respect, we believe this point might be particularly relevant for recovery from the Covid-19 crisis.

Our paper is related to the literature devoted to the UK productivity puzzle.[7] This literature has so far considered many complementary reasons for the poor post-2008 performance relative to the long-term trend. Among these are: measurement errors in output (Grice, 2012; Goodridge, Haskel, and Wallis, 2016); productivity losses in specific sectors (Riley, Rincon-Aznar, and Samek, 2018); labour hoarding (Martin and Rowthorn, 2012); capital shallowing (Pessoa and Van Reenen, 2014; Goodridge, Haskel, and Wallis, 2016; Riley, Rincon-Aznar, and Samek, 2018); the impact of badly measured intangible capital (Goodridge, Haskel, and Wallis, 2013); changes to firm entry and exit behaviour in the context of an impaired financial sector (Riley, Bondibene, and Young, 2013; Barnett *et al.*, 2014; Riley, Rosazza-Bondibene, and Young, 2014); a

[6] We consider the time frame 2003–13 in our analysis for better comparability with previous studies on the UK productivity puzzle.
[7] See Bryson and Forth (2016) and McCann (2018) for literature reviews.

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lengthening of the left tail of poorly performing firms in the productivity distribution (Andrews, Criscuolo, and Gal, 2015); and a slowdown among high-performing firms in the right tail of the distribution (Schneider, 2018). However, while there are many proposed culprits and some fit better than others certain features of the puzzle, there is a lack of consensus on some key elements of the productivity downturn, while we know little about to what extent the puzzle is demand- and/or supply-driven and the macro role played by markups (De Loecker, Eeckhout, and Unger, 2020).[8]

Our paper is also related to the literature on heterogeneous markups and productivity inspired by Hall (1986) and Olley and Pakes (1996) and further developed in Ackerberg, Caves, and Frazer (2015), De Loecker *et al.* (2016) and Forlani *et al.* (2016). More specifically, in our analysis we estimate a quantity-based production function for UK manufacturing using two estimation procedures, the one developed in De Loecker *et al.* (2016) (henceforth DGKP) and the one described in Forlani *et al.* (2016) (henceforth FMMM). These two methods are similar in their motivation to disentangle heterogeneity in revenue TFP into supply-side differences between firms, notably TFP-Q, from demand-side differences in prices which could be due to differences in input and/or output quality, demand and markups. As for services, we instead estimate revenue-based production functions by building on either the restricted version of the model introduced in FMMM or the more standard Wooldridge (2009) approach (henceforth WLD). Again, our results are largely unaffected by whether we use one or the other estimation method.

The remainder of this paper is structured as follows. Section II presents key highlights of the underlying model and related TFP-R and labour productivity decompositions. Section III is devoted to some operational details while section IV describes the data sets used and provides some summary statistics. Section V presents our key results for both manufacturing and services while section VI contains a number of additional findings showing the robustness of our results. Finally, section VII concludes. Further details about the data and additional results are reported in Appendix S1.

II. The MULAMA model

In this section we presents key highlights of the underlying firm model, and related TFP-R and labour productivity decompositions, that we subsequently use in our analyses of the productivity performance of UK firms.

This section follows FMMM and in particular we provide here the single-product firm version of the model. See FMMM for the multi-product firm extension of the model. The model is labelled MULAMA because of the names of the three heterogeneities it allows for: markups **MU**, demand **LAM**bda and quantity TFP **A**. FMMM also provide an estimation procedure to quantity markups, demand and quantity TFP that we employ in our analysis. At the same time, the estimation procedure developed in DGKP is also

[8]For example, in manufacturing there is not a consensus on whether the labour productivity puzzle is also a total factor productivity puzzle. More specifically, Goodridge, Haskel, and Wallis (2016) build upon an aggregate-level growth accounting approach and find that labour productivity in manufacturing has declined also because of a decline in total factor productivity. By contrast, Harris and Moffat (2017) build upon a firm-level approach and find that the labour productivity puzzle in manufacturing is mainly driven by a decline in intermediates intensity while TFP growth continued.

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consistent with the MULAMA model and we employ that estimation procedure as well to corroborate the robustness of our findings. Furthermore, the MULAMA model allows for an exact decomposition of revenue TFP in terms of the underlying heterogeneities. In addition, we develop below a decomposition of labour productivity which generalizes the standard formula used in growth accounting exercises to the presence of heterogeneity in demand and markups.

Measuring demand

In what follows we index firms by i and time by t and denote with lowercase the log of a variable (e.g. r_{it} denotes the natural logarithm of revenue R_{it}). Standard profit maximization (marginal revenue equal to marginal costs) implies that the elasticity of revenue R_{it} with respect to quantity Q_{it} is one over the profit-maximizing markup:

$$\frac{\partial r_{it}}{\partial q_{it}} = \underbrace{\frac{\partial R_{it}}{\partial Q_{it}}}_{\text{marginal revenue}} \frac{Q_{it}}{R_{it}} = \underbrace{\frac{\partial C_{it}}{\partial Q_{it}}}_{\text{marginal cost}} \frac{Q_{it}}{P_{it}Q_{it}} = \frac{\frac{\partial C_{it}}{\partial Q_{it}}}{P_{it}} = \frac{1}{\mu_{it}}, \tag{1}$$

where $\mu_{it} = P_{it}/\frac{\partial C_{it}}{\partial Q_{it}}$ is the profit-maximizing markup. This result comes from static profit maximization and holds under different assumptions about demand (representative consumer and discrete choice models) and product market structure (monopolistic competition, monopoly and standard forms of oligopoly).

Despite the log revenue function, i.e. the function relating log revenue to log quantity, being both unknown and potentially different across firms, equation (1) provides us with the slope of the firm-specific log revenue function while data on the actual log revenue r_{it} and log quantity q_{it} referring to firm i provide us with a point where such log revenue function cuts through the (q, r) space. If we now linearize the log revenue function around the observed data point (q_{it}, r_{it}) with a slope given by $\frac{1}{\mu_{it}}$ we can uniquely pin down an intercept for this linearized log revenue function on the r axis. We use such intercept $\tilde{\lambda}_{it}$ as a measure of firm-specific demand:[9]

$$\tilde{\lambda}_{it} \equiv r_{it} - \frac{\partial r_{it}}{\partial q_{it}} q_{it} = r_{it} - \frac{q_{it}}{\mu_{it}}. \tag{2}$$

Given our definition of $\tilde{\lambda}_{it}$ observed firm log revenue is simply

$$r_{it} = \tilde{\lambda}_{it} + \frac{1}{\mu_{it}} q_{it}, \tag{3}$$

and so $\tilde{\lambda}_{it}$ is a firm-specific log revenue shifter corresponding to the log price firm i would face if selling one unit of its product.[10]

[9]To simplify notation we ignore components that are constant across firms in a given time period or within a product category. Those constants will be captured in our empirical analysis by a suitable set of dummies.

[10]At the intercept point $q_{it} = 0$ and so we have $Q_{it} = 1$ from which $R_{it} = P_{it}$ and $r_{it} = p_{it} = \tilde{\lambda}_{it}$. Note this has no implications whatsoever about the presence/absence of a choke price.

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While being general and intuitive, this measure of firm-specific demand also maps to more formal and explicit differences in the underlying structure of preferences. In particular, FMMM show that $\tilde{\lambda}_{it} = \frac{\lambda_{it}}{\mu_{it}}$ where λ_{it} is a parameter characterizing differences in utility derived from the consumption of products sold by different firms. More specifically, consider a representative consumer who maximises at each point in time t a differentiable utility function $U(.)$ subject to budget B_t:

$$\max_{Q} \left\{ U\left(\tilde{Q}\right) \right\} \text{ s.t. } \int_i P_{it} Q_{it} \mathrm{d}i - B_t = 0,$$

where $\tilde{Q}$ is a vector of elements $\Lambda_{it} Q_{it}$ and $\lambda_{it} = \log(\Lambda_{it})$. Therefore, while the representative consumer chooses quantities Q, these quantities enter into the utility function as $\tilde{Q}$ and Λ_{it} can be interpreted as a measure of the perceived quality/appeal of a particular variety. In our analysis we employ λ_{it} as a complementary measure of firm-specific demand and sometimes refer to $\tilde{\lambda}_{it}$ as markup-adjusted demand.[11]

Measuring markups

As far as markups are concerned, FMMM build upon a result, first highlighted in Hall (1986) and implemented in De Loecker and Warzynski (2012) and DGKP among others, based on cost-minimization of a variable input free of adjustment costs (materials in our empirical implementation) and price-taking behaviour on the input side (the cost of materials W_{Mit} is allowed to be firm-time specific but it is given to the firm). The proof goes as follows. Starting from the definition of marginal cost:

$$\frac{\partial C_{it}}{\partial Q_{it}} = \frac{\partial C_{it}}{\partial M_{it}} \frac{\partial M_{it}}{\partial Q_{it}} = W_{Mit} \frac{\partial M_{it}}{\partial Q_{it}}.$$

Now define the markup as:

$$\mu_{it} \equiv \frac{P_{it}}{\frac{\partial C_{it}}{\partial Q_{it}}}.$$

We thus have:

$$\frac{P_{it}}{\mu_{it}} = W_{Mit} \frac{\partial M_{it}}{\partial Q_{it}}.$$

[11]The interpretation of Λ_{it} as a utility shifter and its relationship with the firm log revenue function are based on a first-order linear approximation around the profit-maximizing solution, i.e. $r_{it} \simeq \frac{1}{\mu_{it}}(q_{it} + \lambda_{it})$. In this respect, FMMM show that such linear approximation holds for any preferences structure that can be used to model monopolistic competition, and for which a well-behaved differentiable utility function exists, as well as to the oligopoly model developed in Atkeson and Burstein (2008) and further refined in Hottman, Redding, and Weinstein (2016). This includes standard CES preferences as well as generalized CES preferences (Spence, 1976), CARA preferences (Behrens *et al.*, 2014), HARA preferences (Haltiwanger, Kulick, and Syverson, 2018), Translog preferences (Feenstra, 2003) as well as the class of Variable Elasticity of Substitution preferences discussed in Zhelobodko *et al.* (2012) and Dhingra and Morrow (2019). Finally, FMMM provide examples suggesting that a log-linear approximation of the revenue function, which is behind both the construction of $\tilde{\lambda}_{it}$ and its interpretation as a markup-adjusted measure of product appeal, works well for many utility specifications.

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Multiplying by Q_{it} and dividing by M_{it} on both sides we get:

$$\frac{P_{it}Q_{it}}{M_{it}\mu_{it}} = \frac{R_{it}}{M_{it}\mu_{it}} = W_{Mit}\frac{\partial M_{it}}{\partial Q_{it}}\frac{Q_{it}}{M_{it}} = W_{Mit}\frac{\partial m_{it}}{\partial q_{it}}.$$

Re-arranging, we finally have:

$$\mu_{it} = \frac{\frac{\partial q_{it}}{\partial m_{it}}}{\frac{W_{Mit}M_{it}}{R_{it}}} = \frac{\frac{\partial q_{it}}{\partial m_{it}}}{s_{Mit}}. \tag{4}$$

The simple rule to pin down markups is consistent with many hypotheses on product market structure (monopolistic competition, monopoly and standard forms of oligopoly) and consists in taking the ratio of the output elasticity of materials ($\frac{\partial q_{it}}{\partial m_{it}}$) to the share of materials in revenue $\left(s_{Mit} \equiv \frac{W_{Mit}M_{it}}{R_{it}}\right)$. Measuring the output elasticity of materials requires estimation of the coefficients of the production function while the share of materials in revenue is directly observable in most data sets (including ours). For example, in the case of a Cobb–Douglas production function with three inputs (labour L, materials M and capital K) and with (log) quantity TFP being labeled as a_{it}, log quantity is:

$$q_{it} = \alpha_L l_{it} + \alpha_M m_{it} + \alpha_K k_{it} + a_{it}, \tag{5}$$

and so the output elasticity of materials is constant and equal to α_M meaning that $\mu_{it} = \frac{\alpha_M}{s_{Mit}}$. When instead considering a Translog production function log quantity is:

$$q_{it} = \sum_{x\in\{m,l,k\}}\left[\alpha_X x_{it} + \frac{1}{2}\alpha_{XX}(x_{it})^2\right] + \alpha_{MK}m_{it}k_{it} + \alpha_{ML}m_{it}l_{it} + \alpha_{LK}l_{it}k_{it} + a_{it}, \tag{6}$$

and so:

$$\mu_{it} = \frac{\alpha_M + \alpha_{MM}m_{it} + \alpha_{ML}l_{it} + \alpha_{MK}k_{it}}{s_{Mit}}.$$

With estimates of the production function coefficients at hand, (4) can be used to recover firm-specific markups. At the same time, with markups as well as log quantity and log revenue, (2) can be used to get the demand measures $\tilde{\lambda}_{it}$ and λ_{it}.

Quantity TFP

The last step to close the model involves estimating the parameters of the production function and so recover quantity TFP a_{it} and subsequently markups and demand as explained above. There are many different hypotheses, and related estimation procedures, one can use in order to achieve this and in what follows we employ two techniques.

One readily available approach to estimate the production function, that is consistent with the MULAMA model, is provided in DGKP. This method relies on the popular proxy variable approach pioneered by Olley and Pakes (1996) and in particular, starting from the conditional input demand for materials, adds to such function a number of observables

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(prices and market shares in particular) to proxy for unobservables (markups and demand heterogeneity in our framework) while further imposing invertibility of the conditional input demand for materials. We describe this approach in Appendix S1.

In an attempt to address some identification issues related to the DGKP approach, FMMM develop an alternative estimation method that does not rely on the proxy variable approach. More specifically, FMMM use both the first-order approximation of the log revenue function and the production function to recover technology parameters. The key disadvantage of this method is that one has to be explicit about the process governing the evolution of demand. We describe this approach in Appendix S1.

TFP-R decomposed

To appreciate how the MULAMA model is useful in linking revenue TFP and quantity TFP note that, with standard Hicks-neutral TFP, one can write the log of the production function as $q_{it} = \overline{q}_{it} + a_{it}$ where $\overline{q}_{it}$ is an index of input use that we label scale.[12] Revenue TFP is simply log revenue minus scale $\text{TFP}_{it}^{R} \equiv r_{it} - \overline{q}_{it} = a_{it} + p_{it}$, and it is also equal to quantity TFP plus log price. Using equation (3) to substitute for r_{it} along with $\tilde{\lambda}_{it} = \frac{\lambda_{it}}{\mu_{it}}$ we get:

$$\text{TFP}_{it}^{R} = \frac{a_{it}}{\mu_{it}} + \frac{\lambda_{it}}{\mu_{it}} + \frac{1-\mu_{it}}{\mu_{it}}\overline{q}_{it}, \tag{7}$$

meaning that TFP_{it}^{R} is a (non-linear) function of quantity-based TFP a_{it}, demand λ_{it}, the markup μ_{it} and production scale $\overline{q}_{it}$. (7) can also be made linear by considering markup-adjusted quantity TFP and scale $\left(\tilde{a}_{it} = \frac{a_{it}}{\mu_{it}} \text{ and } \tilde{\overline{q}}_{it} = \frac{(1-\mu_{it})\overline{q}_{it}}{\mu_{it}}\right)$:

$$\text{TFP}_{it}^{R} = \tilde{a}_{it} + \tilde{\lambda}_{it} + \tilde{\overline{q}}_{it}, \tag{8}$$

so that TFP_{it}^{R} differences across firms and time can be decomposed as the sum of differences in $\tilde{a}_{it}$, $\tilde{\lambda}_{it}$ and $\tilde{\overline{q}}_{it}$. In particular, using Δ to denote changes between $t-1$ and t:

$$\Delta\text{TFP}_{it}^{R} = \Delta\tilde{a}_{it} + \Delta\tilde{\lambda}_{it} + \Delta\tilde{\overline{q}}_{it}. \tag{9}$$

Labour productivity decomposed

TFP, whether of the quantity or revenue flavour, is not the only productivity measure of interest to economists and policymakers. Labour productivity measured as output per worker or per hour worked is widely used and is often more closely related to wages and living standards. In many empirical settings researchers use a simple growth accounting method to attribute (log) labour productivity changes to changes in the labour input, other inputs and TFP building on the Cobb–Douglas production function:

$$r_{it} = q_{it} + p_{it} = \alpha_L l_{it} + \alpha_M m_{it} + \alpha_K k_{it} + \underbrace{a_{it} + p_{it}}_{\text{TFP}_{it}^{R}},$$

[12]For example, with a Cobb–Douglas production technology $\overline{q}_{it} = \alpha_L l_{it} + \alpha_M m_{it} + \alpha_K k_{it}$.

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where $a_{it} + p_{it}$ is nothing else than revenue TFP. By subtracting l_{it} from both sides while rearranging and considering time changes Δ, we have the following labour productivity (LP_{it}) decomposition:

$$\Delta \text{LP}_{it} = \Delta(r_{it} - l_{it}) = (\alpha_L - 1)\Delta l_{it} + \alpha_M \Delta m_{it} + \alpha_K \Delta k_{it} + \Delta \text{TFP}^R_{it}. \tag{10}$$

The equivalent factor proportions version used in Goodridge, Haskel, and Wallis (2016), Harris and Moffat (2017) and Pessoa and Van Reenen (2014) is:

$$\Delta \text{LP}_{it} = \gamma \Delta l_{it} + \alpha_M \Delta(m_{it} - l_{it}) + \alpha_K \Delta(k_{it} - l_{it}) + \Delta \text{TFP}^R_{it}, \tag{11}$$

where $\gamma = \alpha_L + \alpha_M + \alpha_K - 1$ is a parameter measuring returns to scale.

Within the MULAMA model both decompositions can be further developed. More specifically, substituting (9) for ΔTFP^R_{it} in (10) and simplifying leads to:

$$\Delta \text{LP}_{it} = \Delta\left[\left(\frac{\alpha_L}{\mu_{it}} - 1\right) l_{it}\right] + \alpha_M \Delta\left(\frac{m_{it}}{\mu_{it}}\right) + \alpha_K \Delta\left(\frac{k_{it}}{\mu_{it}}\right) + \Delta\left(\frac{a_{it}}{\mu_{it}}\right) + \Delta\left(\frac{\lambda_{it}}{\mu_{it}}\right), \tag{12}$$

while, in the factor proportions version, substituting (9) for ΔTFP^R_{it} in (11) delivers:

$$\Delta \text{LP}_{it} = \Delta\left[\left(\frac{\gamma + 1}{\mu_{it}} - 1\right) l_{it}\right] + \alpha_M \Delta\left(\frac{m_{it} - l_{it}}{\mu_{it}}\right) + \alpha_K \Delta\left(\frac{k_{it} - l_{it}}{\mu_{it}}\right) + \Delta\left(\frac{a_{it}}{\mu_{it}}\right) + \Delta\left(\frac{\lambda_{it}}{\mu_{it}}\right). \tag{13}$$

From (12) and (13) it now appears clearly how changes in labour productivity materialize as a consequence of changes in quantity TFP, demand, markups and input use.

The restricted model and services

Quantity and price data are very often not available to researchers, almost universally for the service sectors where output measures can be particularly problematic (Office for National Statistics, 2007). In such cases, the only available option is to estimate the production function and related TFP using revenue, or value added, as a measure of output, i.e. measure revenue TFP. This raises the issue, discussed above, of the bias in the estimation of production function coefficients coming from any correlation between the underlying prices and inputs use. In this respect, FMMM provide an overall reassuring message.

More specifically, FMMM find that more standard revenue TFP measures obtained using revenue as a measure of output are reasonably well correlated with revenue TFP measures obtained using quantity as a measure of output; something we will show later on holds in our data too.

FMMM further show that the key disadvantage of not having price and quantity data is the fact that one can no longer disentangle quantity TFP a from demand λ but only retrieve a composite of the two: $\omega_{it} = a_{it} + \lambda_{it}$. However, markups can still be computed

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from the estimated production function coefficients using (4) while the TFP-R and labour productivity decompositions provided above still hold by replacing the distinct a and λ terms with a unique ω term. For example, considering (7) we have:

$$\mathrm{TFP}_{it}^{R}=\frac{\omega_{it}}{\mu_{it}}+\frac{1-\mu_{it}}{\mu_{it}}\overline{q}_{it}, \tag{14}$$

which provides a formula to retrieve ω_{it} from measures of revenue TFP, markups and scale; measures that only require estimates of the production function coefficients. At the same time, for example, (13) becomes:

$$\Delta\mathrm{LP}_{it}=\Delta\left[\left(\frac{\gamma+1}{\mu_{it}}-1\right)l_{it}\right]+\alpha_M\Delta\left(\frac{m_{it}-l_{it}}{\mu_{it}}\right)+\alpha_K\Delta\left(\frac{k_{it}-l_{it}}{\mu_{it}}\right)+\Delta\left(\frac{\omega_{it}}{\mu_{it}}\right). \tag{15}$$

FMMM label this restricted version of the model MUOMEGA in reference to the two heterogeneities it allows for, markups (MU) and a composite of TFP-Q and λ (OMEGA). FMMM also develop an estimation procedure for the restricted model.

III. Some operational details

In this section we provide details about how we apply the models developed in the previous section to the data. Operationally, we distinguish between manufacturing (for which data on quantity and prices are available) and services. We also discuss the issue of aggregation and in particular composition effects and weighting.

Manufacturing

As far as manufacturing is concerned, we consider as baseline the implementation of the MULAMA model and related decompositions based on the DGKP estimation method applied to the Cobb–Douglas production function (5) on the single-product firm sample. However, we also present results based on the FMMM estimation method, also in Cobb–Douglas form, as well as findings obtained from the Translog production function (6) and the sample of multi-product firms for robustness. Our key findings are little affected by whether we use the DGKP or the FMMM estimation procedure, by whether we use a Cobb–Douglas or a Translog production function and whether we use the single-product firm sample or the multi-product firm sample.

As customary in productivity analyses, we correct (in all estimations) for the presence of measurement error in output (quantity and revenue) and/or unanticipated (to the firm) shocks using the method described in DGKP and FMMM. We also consider a full battery of eight-digit product dummies, as well as year dummies in our production function estimations. Indeed, quantity in the data is measured in units (kilograms, litres, number of items, etc.) that are specific to each eight-digit product and so quantity TFP a_{it} can be reasonably compared across firms and time only within an eight-digit product category.

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For similar reasons, also λ_{it} can be reasonably compared across firms and time only within an eight-digit product category.

In terms of production function estimations we are forced, by sample constraints, to run a single estimation across the whole manufacturing firms sample instead of by two-digit industry groupings. As explained afterwards, we need firms to be in both the Prodcom and ARDx[13] data sets, described below, while also requiring information on one and two period lags for all variables. In this respect, results obtained using the more flexible Translog production function should allay concerns over the heterogeneity in output elasticities across firms and industries. At the same time, we show later on that patterns of various TFP-R measures, as well as of value added per worker and output per worker, are very similar when comparing our estimation sample to the full set of manufacturing firms available in the ARDx data set.

Services

As far as service industries are concerned, we consider as baseline the revenue TFP estimations, and related MUOMEGA model decompositions, based on the WLD approach applied to the Cobb-Douglas production function (5). We also present very similar results based on the FMMM estimation method for the MUOMEGA model, also in Cobb–Douglas form.

Again, as customary in productivity analyses, we correct (in all estimations) for the presence of measurement error in revenue and/or unanticipated (to the firm) shocks using the method described in DGKP and FMMM. Production function estimations are run separately for each NACE Section (11 in total) and include a full battery of two-digit industry dummies as well as year dummies.

Composition effects and weighting

There are reasonable concerns about composition effects as the ARDx firm sample changes over time, and particularly so from 2007 to 2008 when the ONS switched from producing the Annual Respondents Database to the Annual Business Survey. Therefore we present, as baseline, results for what we label the 'within sample' which compares the mean of within-firm changes between $t-1$ and t. The within sample is thus composed of firms present in the data in both $t-1$ and t and, if manufacturing firms, also producing the same product in both years. The within sample allows minimising the impact of sample composition effects, including those related to different units of measurement for the products of manufacturing firms. We show below that the within sample accounts for the lion's share of overall firm revenue in both $t-1$ and t.

Finally, we choose to present our baseline results using revenue weights, given that our research question is more closely aligned to understanding aggregate changes in productivity rather than for the average firm. We also present below

[13]The Annual Respondents Database X (ARDx) is a data set administrated by the Office for National Statistics.

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robustness results based on employment weights as well as on equal weights, i.e. unweighted.

Operationally, we calculate an index for each variable of interest after averaging within-firm changes between $t-1$ and t:

$$\Delta\bar{y}_t = \frac{1}{N_t}\sum_{i=1}^{N_t}(y_{it} - y_{it-1})w_{it}, \tag{16}$$

where y_{it} is a variable of interest (TFP-Q, TFP-R, λ, μ, etc.), $\Delta\bar{y}_t$ is the weighted average of within firm changes in y_{it}, $w_{it} = \frac{1}{2}(R_{it} + R_{it-1})$ are the weights computed using the average firm revenue between $t-1$ and t, and N_t is the number of firms present in the data in both $t-1$ and t. We use this formula to construct the index of changes, setting the base year to 2008 for manufacturing and 2007 for services.

IV. Data and descriptives

Data

The core data required to estimate firm-level revenue TFP using standard methods comprise revenue, employment costs, intermediate inputs and capital stock. For these variables we turn to the Office for National Statistics (ONS) Annual Respondents Database X (ARDx).[14] The ARDx is a recently-created dataset for researchers using ONS data via the Virtual Microdata Library and the Secure Data Service. It combines and standardizes data and variables across the period 1998–2017 from two surveys, the Annual Business Survey (ABS) which has been carried out since 2009, and its predecessor, the Annual Business Inquiry (ABI), which was carried out 1998–2008 and used to create the Annual Respondents Database. These are the largest business surveys in the UK and have been used by many UK productivity researchers including Barnett *et al.* (2014), Harris and Moffat (2017) and Riley, Bondibene, and Young (2013). The ABI and ABS are similar in sampling method, structure and questions, and the ARDx was created to provide researchers with a consistent data set across time.

The ARDx covers around two-thirds of UK economic activity, comprising most SIC 2007 sections, except parts of sections A (agriculture) and K (finance), and all of O (public administration and defence), T (activities of households) and U (extraterritorial organizations). The sample frame of the ABS is the Inter-Departmental Business Register (IDBR), a register of firms from HM Revenue and Customs data on VAT and PAYE details. The sample is stratified by SIC 2007 activities (at the four-digit level), employment size and country (England & Wales, and Scotland). A sample of 62,000 of the 2.1 m firms on the IDBR is drawn annually. All firms in the largest employment categories in each cell are selected. Firms in each of the cells including smaller businesses are drawn for two consecutive years only, and then not reselected for at least 2 years afterwards. For the smallest (0-9) employment category, firms are only selected in

[14] Office for National Statistics. Virtual Microdata Laboratory (University of the West of England), 2017.

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a single year, and then not again for at least 3 years afterwards to ensure that the compliance burden on firms is proportionate. Since we require lagged values of variables in our estimations, we drop these firms and focus on firms with at least 10 employees.

Estimation of quantity TFP and demand for the manufacturing sector requires data on quantities sold and prices, information that is available in the Products of the European Community (Prodcom) dataset.[15] Prodcom is a standardized survey of production across the European Union, collected by national statistical agencies using a 3,500 product list in an eight-digit nomenclature established by Eurostat. The first four digits correspond to the Nomenclature Statistique des Activités Economiques dans la Communauté Européenne (NACE) using revision 1.1 up to 2007 and revision 2 from 2008, and the first six digits to the Classification of Products by Activity (CPA) with the last two digits adding further detail. It covers SIC 2007 sections B (mining) and C (manufacturing) sectors. We exclude section B to focus on manufacturing. The survey captures at least 90% of production in all the four-digit industries covered by the survey.

Illustrating the advantages of highly disaggregated data, Table 1 shows an extract from the 2009 Prodcom list for the six-digit codes 13.10.61: 'Cotton yarn (other than sewing thread)' and 26.20.16: 'Input or output units, whether or not containing storage units in the same housing'. The latter example highlights how it can often be necessary to work with eight-digit data rather than the already quite detailed six-digit level, in order to be confident to compare reasonably similar items. The former example highlights instead how a eight-digit product breakdown can be very precise in terms of narrowing down product definitions and so working at this level of disaggregation allows us to take into account rich differences in technology, demand and degree of competition across finely-defined products.

Around 20,000 firms a year, representing at least 90% of the value of production in each four-digit industry, are surveyed to construct the Prodcom dataset using the IDBR as the sample frame. The sample is stratified by employment size and SIC 2007 four-digit industry. There are three employment band thresholds above which all firms are surveyed (20, 50 and 100), where the cut-off varies between industries. Below that firms are rotated through the sample.

The quantity and value of sales are recorded for each eight-digit product produced by a firm annually.[16] We measure firm-product-year specific prices as the ratio of the value of sales to the quantity and apply a small trimming on the distribution of prices by eight-digit product to get rid of outliers. Prodcom product codes change occasionally over time and we employ the method described in Van Beveren, Bernard, and Vandenbussche (2012) to obtain a time-consistent product classification. Appendix S1 provides more details on the product concordance procedure. We also ensure that the units of measure used to record quantities are consistent over time. Metadata provided by the ONS for Prodcom links each product-year with a unit of measure and where these units change over time within a

[15] Office for National Statistics (2018c).

[16] This introduces a discrepancy with the ARDx. In Prodcom, firms report calendar-year product sales and quantities, while in the ARDx firms can report either calendar year or financial year revenue figures. We deal with this by dropping firms that report values for ARDx sales that are outside a range of ±30% of total Prodcom sales. This also has the effect of removing manufacturing firms with a high proportion of services in revenues.

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TABLE 1

Examples of eight-digit PRODCOM products within six-digit CPA categories

PRODCOM	*Description*
	COTTON YARN (OTHER THAN SEWING THREAD)
13.10.61.32	Yarn of uncombed cotton, not per retail sale, for woven fabrics (excluding for carpets and floor coverings)
13.10.61.33	Yarn of uncombed cotton, not per retail sale, for knitted fabrics and hosiery
13.10.61.35	Yarn of uncombed cotton, not per retail sale, for other uses (including carpets and floor coverings)
13.10.61.52	Yarn of combed cotton, not per retail sale, for woven fabrics (excluding for carpets and floor coverings)
13.10.61.53	Yarn of combed cotton, not per retail sale, for knitted fabrics and hosiery
13.10.61.55	Yarn of combed cotton, not per retail sale, for other uses (including carpets and floor coverings)
	INPUT OR OUTPUT UNITS, WHETHER OR NOT CONTAINING STORAGE UNITS IN THE SAME HOUSING
26.20.16.40	Printers, copying machines and facsimile machines, capable of connecting to an automatic data processing machine or to a network (excluding printing machinery used for printing by means of plates, cylinders and other components, and machines performing two or more of the functions of printing, copying or facsimile transmission)
26.20.16.50	Keyboards
26.20.16.40	Other input or output units, whether or not containing storage units in the same housing

Source: EC RAMON Database (2009 Prodcom List).

product we define a new product, leaving us a total of 5,028 product-units. Some products are reported within Prodcom without quantity data and we drop these products, leaving 3,239 consistent product-units with non-missing quantity data. Our unit of observation is strictly firm-product-unit-year but for ease of exposition we refer to firm-product-year throughout the analysis.

Both data sets cover Great Britain while data for Northern Ireland are held separately and are excluded from our analysis. Our analysis focuses on the period 2003–13 in order to both gain insights into the pre- and post-crisis productivity performance and provide evidence comparable to previous studies. We deflate, as standard, both output and input values from the ARDx using information provided by the ONS. Appendix S1 provides more details on the data sets, the construction of capital stocks and the deflators used in the analysis while Table A4 in Appendix S1 describes the main variables used in our estimations.

Descriptives

We merge the ARDx, capital stock and Prodcom data using a unique identifier for what the ONS refers to as a 'reporting unit'[17] and we refer to as a firm, our unit of analysis.[18]

[17]Large businesses ('enterprises' to the ONS, and the legal entity of the business) may be split into a number of reporting units, while reporting units can comprise a number of local units which are separated geographically. Data in the ARDx are collected at the reporting unit level.

[18]Some authors, e.g. Harris and Moffat (2017), argue that the local unit (plant) is the preferred unit of analysis because it provides cleaner estimates of capital stock due to plant entry and exit within a firm, but this requires apportioning firm-level inputs and outputs to plants, while information on production from Prodcom is available only at the firm level.

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Manufacturing

Although the ARDx is a representative sample of private-sector firms and Prodcom is designed to cover 90% of manufacturing output, there is not perfect overlap between the two data sets, a problem compounded by the requirements of the DGKP and FMMM estimation procedures. More specifically, to estimate the production function for manufacturing firms while using quantity as a measure of output we require/impose:

- non-missing, positive values for employment, total turnover excluding VAT, purchases of goods and materials, capital stock, total wages and salaries from the ARDx
- the firm is in the Prodcom survey
- that Prodcom records a non-zero value for quantity of this product
- the firm produces only 1 product in any given year
- and that firm revenues reported in Prodcom are within 30% of the output calculated using ARDx data

These demands sharply reduce the available sample size and in Appendix S1 we provide more details on the merging process and the various constraints.[19] We label 'final sample' the combined ARDx and Prodcom sample satisfying all our requirements.

We do not think of the final sample as being representative of the broader populations of manufacturing firms and/or single-product firms as selection into the estimation sample is unlikely to be random, particularly reflecting industry characteristics (for the availability of physical quantity data in Prodcom) and firm size (for selection separately into the Prodcom and ARDx surveys with differing stratification bands). Rather, we seek to show that time trends in productivity measures within the group of firms for which we are able to estimate the full MULAMA model (final sample) are similar to those in broader samples. Our first step to do this is to estimate standard two-factor (value added based) and three-factor (revenue-based) production functions, using both the method of ordinary least squares and the WLD approach, on the whole sample of manufacturing firms in the ARDx for which revenue productivity can be estimated ('all variables available'). We report production function coefficients in Table A15 in Appendix S1, and use these to calculate mean revenue-based and value added-based TFP over time for different samples going from the largest ('all variables available') to the final sample we use in our estimations ('.plus data constraints'). We graph the results, along with output per worker and value added per worker, in Figure 1. All the productivity measures we consider indeed display a very similar behaviour across time for the four samples. This builds confidence that the trends in quantity TFP, demand and markups for the wider sample of firms in the ARDx are similar to those we uncover in the final sample.

One final issue we address is related to the ARDx sampling frame changing over time – notably in 2008/9 when SIC 2008 replaced SIC 2004 – leading to concern that comparing firm averages over time, whether weighted on unweighted, will be biased by

[19] In our estimations we also apply some small trimming (top/bottom percentile) of unit prices by product, the capital-to-labour ratio and labour-output ratio by two-digit industry, and drop firm-year observations where the share of materials in output is less than 0.1 or greater than 0.95.

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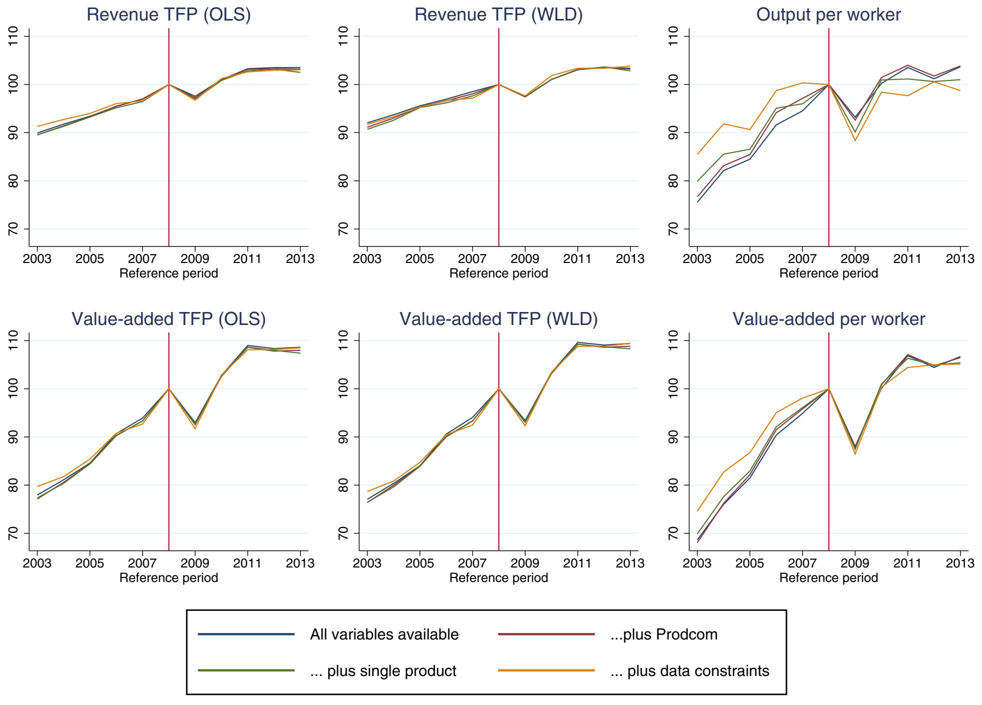

FIGURE 1. Revenue TFP and labour productivity measures by sample, Manufacturing, 2003–13. All revenue TFP and labour productivity measures are indexed: 2008=100. 'All variables available' refer to manufacturing firms in the ARDx that have (i) at least 10 employees and (ii) have the following variables available: employment, total turnover ex. VAT, purchases of goods and materials, capital stock, total wages and salaries. '...plus Prodcom' adds the requirement that the firm-year observation is also in the Prodcom dataset. '...plus single product' adds the requirement that at least 90% of a firm's output at basic prices is accounted for by sales of a single product. '...plus data constraints' adds the requirement that Prodcom measures a non-zero quantity of production, and that firm revenues reported by Prodcom are within 30% of the output calculated from the ARDx. Revenue TFP estimated using ordinary least squares (OLS) or the Wooldridge procedure (WLD) in revenue and value added forms [Colour figure can be viewed at wileyonlinelibrary.com]

changes in the sample composition. Given this, our results focus on within-firm changes over time using an unbalanced panel of firms for which we have observations in both year t and year $t-1$: the within sample.

Table A5 in Appendix S1 shows the number of observations by year corresponding to the final sample and the within sample for manufacturing along with the share of revenue (combined revenue in $t-1$ and t) accounted for by firms in the within sample. While within-sample observations account for fewer than half the available firm-year observations, they account for roughly two-thirds of full-sample revenues. Summary statistics for key variables and MULAMA model estimates (obtained with the DGKP estimation procedure) referring to both samples are provided in Table A6 in Appendix S1.

Services

For services firms we merge the ARDx and capital stock data, using the unique identifier reporting unit, and impose non-missing, positive values for employment, total turnover ex. VAT, purchases of goods and materials, capital stock and total wages and salaries. This

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delivers the final sample for services firms.[20] Again, because of concerns about sampling frame changes, we focus on within-firm changes over time using an unbalanced panel of firms for which we have observations in both year t and year $t-1$: the within sample for services. We also provide similar results using both unweighted and weighted results.

Table A7 in Appendix S1 shows the number of observations by year corresponding to the final sample and the within sample for services along with the share of revenue (combined revenue in $t-1$ and t) accounted for by firms in the within sample. Again, while within sample observations account for fewer than half the available firm-year observations, they account for more than two-thirds of full-sample revenues. Summary statistics for key variables and MUOMEGA model estimates (obtained with the WLD estimation procedure) referring to both samples are provided in Table A8 in Appendix S1.

V. Results

In this Section we provide some highlights of production function estimations and related MULAMA/MUOMEGA model components. We then use the estimated models to analyse the performance of UK firms over the period 2003–13.

Estimation highlights

Estimates of the Cobb–Douglas production function coefficients for manufacturing firms using the DGKP procedure are shown in Table A9 in Appendix S1 while descriptive statistics on the various MULAMA model components are displayed in Table A6 in Appendix S1. In order to provide useful insights for our analysis, while confirming previous findings in FMMM and Jacob and Mion (2020), in Appendix S1 we report on a number of analyses showing that: (i) more productive firms and/or an increase in productivity for a firm (higher a_{it}) are associated with both lower prices and higher markups, i.e. an incomplete pass-through; (ii) firms facing a stronger demand and/or an increase in demand for a firm (higher λ_{it}) are associated with both higher prices and higher markups, so confirming the relevance of λ_{it} as a measure of firm-specific demand.

Moving to services, estimates of the revenue-based production functions obtained using the WLD approach by SIC section are reported in Table A13 in Appendix S1 while descriptive statistics on the various MUOMEGA model components are displayed in Table A8 in Appendix S1.

Manufacturing

We next turn to our main results. For manufacturing, we find it best to use the year 2008 to define the pre- and post-crisis periods.

[20]We also apply, in line with the manufacturing analysis, a small trimming based on the top/bottom percentiles of the capital-to-labour ratio and labour-output ratio by two-digit industry while dropping firm-year observations where the share of materials in output is less than 0.1 or greater than 0.95.

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TABLE 2

Manufacturing. Changes of revenue TFP and its components over the period 2003–13

	Δ *TFP-R* (*WLD*)	Δ *TFP-R* (*DGKP*)	Δa	Δp	$\Delta\lambda$	$\Delta\omega$	$\Delta\mu$	Δ *scale*	*Obs*
2004	0.007	0.021	0.008	0.013	0.232	0.240	0.020	0.040	641
2005	0.011	−0.004	−0.014	0.010	0.029	0.014	0.002	0.021	564
2006	0.020	0.016	0.006	0.010	0.094	0.100	0.007	0.021	617
2007	0.012	0.020	0.003	0.017	0.087	0.090	0.006	0.029	594
2008	0.028	0.022	0.044	−0.022	0.280	0.324	0.028	−0.037	401
2009	−0.023	−0.022	−0.064	0.042	−0.221	−0.284	−0.023	−0.071	443
2010	0.033	0.028	0.012	0.016	−0.009	0.003	−0.000	0.042	496
2011	0.026	0.024	0.023	0.001	0.305	0.328	0.027	0.019	450
2012	−0.008	−0.015	−0.014	−0.001	−0.043	−0.057	−0.003	0.017	478
2013	0.011	0.015	−0.001	0.016	0.187	0.186	0.015	0.024	477
2003–08	0.015	0.016	0.009	0.007	0.143	0.152	0.013	0.016	2,817
2008–13	0.008	0.006	−0.009	0.015	0.045	0.036	0.003	0.007	2,344

Notes: The table shows mean revenue-weighted changes from $t-1$ to t, for the manufacturing firms within sample, of WLD and DGKP revenue TFP, of real prices p as well as of the various components of the revenue TFP non-linear decomposition following from equation (7) applied to the DGKP revenue TFP. The final two rows show the mean of changes over the two periods using all the annual observations shown above.

We report in Table 2 mean revenue-weighted changes from $t-1$ to t, referring to the manufacturing firms within sample, in DGKP revenue TFP and its components building on the non-linear decomposition of equation (7). We also report (column 1) mean revenue-weighted changes in WLD revenue TFP as well as the mean revenue-weighted changes in real prices (column 4).[21] First, we see a similar trend for the DGKP revenue TFP, reported in column 2, to that illustrated across larger samples in Figure 1. The DGKP measure rises at a rate of 1.6 percentage points (pp) a year from 2003 to 2008, then falls by 2.2 points in 2008/9, averaging across the 2008–13 post-crisis period at a rate of 0.6 pp per year, and leaving it 5 points below the pre-crisis trend by 2013. The WLD measure displays a similar pattern: growth of 1.5 pp a year through 2008, a drop of 2.3 pp in 2008/9 and growing over the 2008–13 post-crisis period at a rate of 0.8 points per year. These results are in line with the dismal post-crisis outcomes for UK productivity containing a strong productivity, and in particular revenue TFP, component. However, this paper's contribution is to disentangle the underlying causes of this revenue TFP drop and in particular assess whether and how changes in quantity TFP, demand and markups have generated the fall.

In this respect, columns 3 and 4 of Table 2 provide evidence that quantity TFP a actually slowed more than revenue TFP in the post-crisis period. The average pre-crisis TFP-Q growth rate of 0.9% turned into a −0.9% growth rate post-crisis leading to marked 9% shortfall with respect to the pre-crisis trend by 2013. At the same time real prices increased substantially more after 2008, switching from a 0.7% growth rate pre-crisis to a 1.5% growth rate post-crisis. Revenue TFP changes (column 2), are the sum of quantity TFP changes (column 3) and real price changes (column 4), and so the stronger real prices

[21] In the Online Appendix we explain how we compute real price changes as the difference between nominal price changes we observe in the data and ONS price index changes.

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increase post-2008 helped to contain the fall in revenue TFP to a 5 points shortfall with respect to the pre-crisis trend by 2013.

Without information on demand and markups, one would be left wondering what caused the increase in real prices and how quantity TFP and real price changes translate into firms' profit margins and scale of operations. In this respect, column 5 indicates that demand (as measured by changes in λ) also plunged in 2008–09 and overall slowed down with respect to the pre-crisis growth trend. Therefore, the increasing real prices post-2008 are likely related to firms passing to consumers the increasing production costs driven by the declining quantity TFP. The pass-through is incomplete as shown by both the difference between the TFP-Q drop and the real prices increase with respect to the trend (1.8% drop in TFP-Q and 0.8% increase in real prices) and by the decline in markups in column 7. Indeed, markups sharply declined in 2008-9 and slowed down their growth ever since. One important element to stress at this point is that the decline in demand, as measured by λ, is on top of the negative effect on sales produced by increasing real prices post-2008. Indeed, changes in λ measure changes in demand for the same price (and markup), i.e. changes in the underlying demand curve.

Therefore the depth of the crisis, and in particular its overall impact on sales, production and input use, has been particularly severe due to both a supply (TFP-Q) and a demand (λ) downturn. This is, for example, reflected in the use of inputs by firms in column 8 (scale). More specifically, the growth rate of the average input bundle turned from a 1.6% pre-crisis growth rate to a 0.7% post-crisis growth rate, leading to a 4.5% shortfall with respect to the pre-crisis trend. This is reflected also in the combined TFP-Q and demand MULAMA component $\omega = a + \lambda$ (column 6) summarizing the negative supply and demand shocks. In terms of broader implications, the fact that in 2013 scale was up by 3.1% and quantity TFP was down by 4.4% with respect to their 2008 levels implies, given that (log) quantity is equal to TFP-Q plus scale at the firm level as well as in our aggregation, that quantities sold in 2013 were still 1.3% below their levels back in 2008.

Figure 2 presents the results graphically. We construct an index for each variable, setting 2008 as the reference year with a value of 100 so that the graph shows the percentage deviation in the index. Figure 2 also provides two regression lines obtained by fitting index yearly changes between 2003 and 2008 (left regression line) and changes between 2009 and 2013 (right regression line). Panels (a) and (b) show quite neatly the break in WLD and DGKP revenue productivity growth before and after 2008 while panels (c) and (d) highlight the more severe downturn in quantity TFP and the mitigating effect of real prices. At the same time, panels (e) and (f) show the downturn in demand and the overall combined change in the pattern of ω. Furthermore, panels (f) and (g) display the post-2008 decline in the evolution of markups and production scale. Finally, Table A18 in Appendix S1 shows formal Chow test results regarding the presence of a structural break for some key variables. As can be appreciated from Table A18, there is indeed strong support for the presence of a structural break in 2008.

A common approach in the literature on the UK productivity puzzle is to decompose the shortfall in labour productivity into contributions of changes in factor inputs and TFP or, to be more precise, factor inputs and revenue TFP as highlighted by equation (11)

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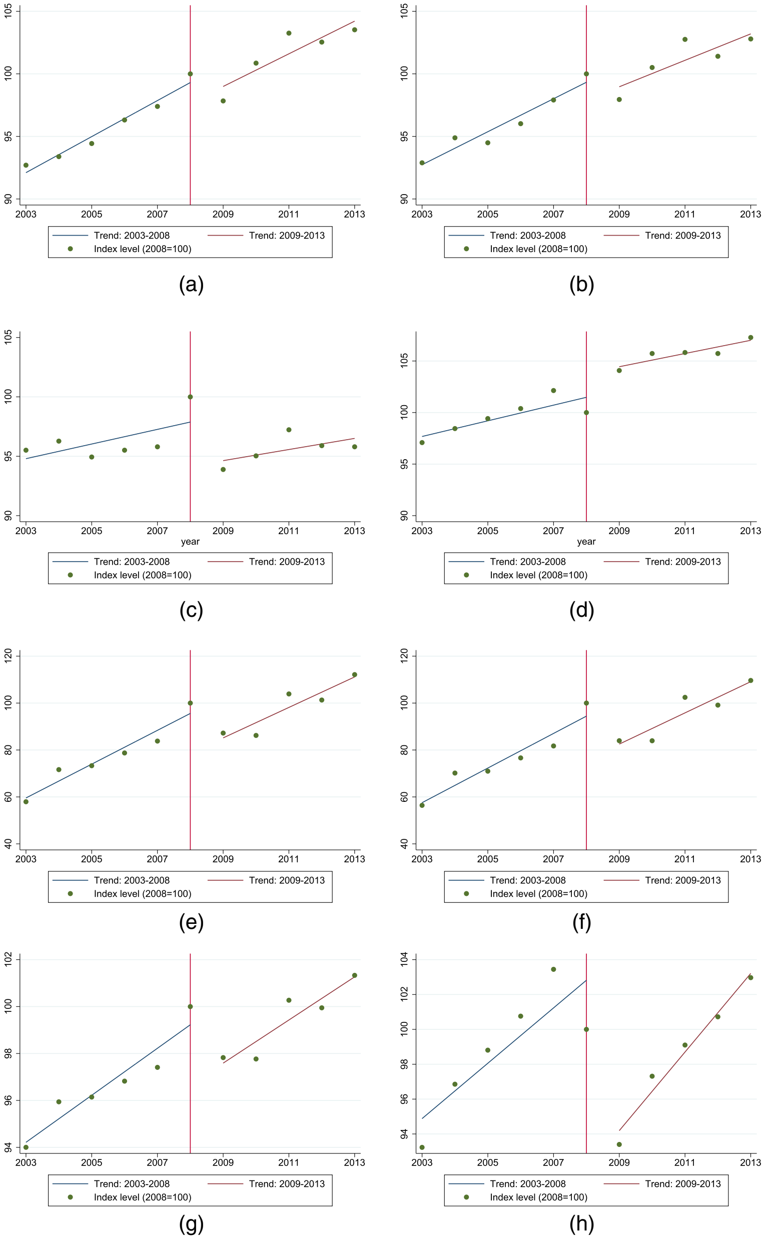

FIGURE 2. Manufacturing. Evolution of revenue TFP and its components over the period 2003-13. Indices (2008=100) calculated using revenue-weighted changes between $t-1$ and t for the within sample of manufacturing firms. Panels (a) and (b) refer to revenue TFP computed using the WLD method and DGKP method, respectively. Panels (c)-(h) show real prices and components of the DGKP revenue TFP following from equation (7). (a) WLD rev TFP; (b) DGKP rev TFP; (c) TFPQ a; (d) Real price p; (e) Demand λ; (f) Composite ω; (g) Markups μ; (h) Production scale [Colour figure can be viewed at wileyonlinelibrary.com]

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in section II. Growth accounting exercises using sectoral national accounts data find that the labour productivity puzzle turns out to be a revenue TFP puzzle (Goodridge, Haskel, and Wallis, 2013). That is, after accounting for changes to capital and labour inputs, the bulk of the 'lost' growth over 2008–13 was due to a slower rate of revenue TFP growth. A paper closer to ours (Harris and Moffat, 2017) uses a bottom-up econometric approach that estimates revenue-based production functions to obtain input parameters and firm-level TFP.[22] Harris and Moffat (2017) find that while in services the decline in labour productivity growth is mostly the result of a decline in revenue TFP growth, in manufacturing there is no revenue TFP puzzle: weighted plant-level revenue TFP barely changed or grew in the 2008–12 period. Instead, a measured 19% decline over 2007–12 in labour productivity is entirely due to changes in the intensity of inputs and in particular the log intermediates to labour ratio $\Delta(m_{it} - l_{it})$ in (11).

Table 3 shows this standard labour productivity decomposition over the period 2003–13 for our revenue-weighted manufacturing firms within sample. Results indicate that manufacturing labour productivity growth in the period 2003–08 was around 2.7 pp a year and, while experiencing significant drops in 2008 and 2009, increased on average by only 1.2 pp a year in the period 2008–13 ending up almost 8% below its pre-crisis trend (more if considering 2003–07 as the baseline period).[23] Column 2 of Table 3 indicates that the main culprit of this under-performance is the drop in revenue TFP growth which changed from about 1.8 pp a year in the period 2003–08 to 0.6 pp per year post-2008, i.e. $[(1.8 - 0.6)/(2.7 - 1.2)] = 80\%$ of the labour productivity growth slowdown.[24] The remaining 20% is almost entirely accounted for by a reduction of the log intermediates to labour ratio, i.e. the term $\Delta(m - l)$.

Table 4, based on the more involved decomposition provided by equation (13) in section II, provides deeper insights on the decline in labour productivity by highlighting the role of demand, quantity TFP and markups. Markup-adjusted TFP-Q barely changed its growth rate in the two periods 2003–08 and 2008–13 while the largest growth rate drop in the whole table is related to markup-adjusted demand $\tilde{\lambda}$ experiencing a decline from the 16.9 pp per year average over 2003–08 to only 5.9 pp post-2008. At the same time, the related slowdown of markups seen in Table 2 helped to contain the fall in labour productivity through an increase in the average yearly growth rate of the markup-adjusted labour term $(\Delta[(\gamma + 1/\mu - 1)l])$ and intermediates over labour term $(\alpha_M \Delta(m - l/\mu))$.[25] Markup-adjusted capital over labour changes only weakly contributed throughout. To

[22] Harris and Moffat (2017) build on previous work that estimates plant-level TFP (Harris and Drinkwater, 2000).

[23] In our analysis we use the firm wage bill, not the number of workers, as a measure of the labour input because we do not want potential changes in worker quality to affect the results. However, to show how changes in demand, TFP-Q and markups are important for labour productivity, it makes little sense to consider the (log of the) ratio between revenue and the wage bill on the left-hand side of the decomposition. Instead we use, in our labour productivity decompositions, the (log) number of full-time-equivalent employees as a measure of the labour input and, in order to make sure that the decomposition goes through, we borrow our estimate of the output elasticity of labour, $\hat{\alpha}_L$, and recompute TFP-Q, TFP-R and scale accordingly. As can be appreciated from Table 3, this makes little difference in terms of the patterns of TFP-Q, TFP-R and scale so far discussed.

[24] Numbers for DGKP revenue TFP in column 2 of Tables 2 and 3 are slightly different because in the latter case we use, as indicated in a previous footnote, the number of employees rather than the wage bill as a measure of the labour input.

[25] From the expressions of these two terms it appears clearly how a reduction in markups μ increases both. Markups are endogenous in the MULAMA/MUOMEGA models and their equilibrium level (determined by profit

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TABLE 3

Manufacturing. Standard labour productivity decomposition (factor proportions version) over the period 2003–13

	$\Delta(r-l)$	Δ *TFP-R (DGKP)*	$\gamma\Delta l$	$(\alpha_M)\Delta(m-l)$	$(\alpha_K)\Delta(k-l)$	*Obs*
2004	0.062	0.035	−0.000	0.026	0.001	641
2005	0.012	0.004	0.000	0.007	0.001	564
2006	0.044	0.023	−0.000	0.024	−0.002	617
2007	0.040	0.019	0.000	0.021	0.000	594
2008	−0.035	0.006	0.000	−0.038	−0.002	401
2009	−0.092	−0.046	−0.000	−0.042	−0.004	443
2010	0.118	0.042	−0.000	0.074	0.002	496
2011	0.038	0.030	0.000	0.009	−0.001	450
2012	−0.012	−0.008	0.000	−0.004	0.000	478
2013	0.007	0.011	0.000	−0.005	0.000	477
2003–08	0.027	0.018	0.000	0.009	−0.001	2,817
2008–13	0.012	0.006	0.000	0.006	−0.000	2,344

Notes: See equation (11) in section II for the derivation of this standard labour productivity decomposition. Final two rows show the mean of changes over the two periods using all the annual observations shown above. Computations refer to revenue-weighted changes for the within sample of manufacturing firms.

TABLE 4

Manufacturing. More detailed labour productivity decomposition (factor proportions version) over the period 2003–13

	$\Delta(r-l)$	$\Delta(a/\mu)$	$\Delta(\lambda/\mu)$	$\Delta\left[\left(\frac{\gamma+1}{\mu}-1\right)l\right]$	$\alpha_M\Delta\left(\frac{m-l}{\mu}\right)$	$\alpha_K\Delta\left(\frac{k-l}{\mu}\right)$	*Obs*
2004	0.062	−0.056	0.300	−0.139	−0.042	−0.001	641
2005	0.012	−0.012	0.004	0.007	0.012	0.001	564
2006	0.044	0.044	0.050	−0.053	0.005	−0.002	617
2007	0.040	−0.060	0.138	−0.035	−0.003	−0.001	594
2008	−0.035	−0.124	0.357	−0.151	−0.112	−0.005	401
2009	−0.092	0.011	−0.312	0.171	0.040	−0.002	443
2010	0.118	−0.020	0.082	−0.012	0.066	0.002	496
2011	0.038	−0.103	0.354	−0.150	−0.061	−0.003	450
2012	−0.012	0.002	−0.071	0.039	0.017	0.001	478
2013	0.007	−0.082	0.234	−0.091	−0.054	−0.001	477
2003–08	0.027	−0.040	0.169	−0.074	−0.027	−0.002	2,817
2008–13	0.012	−0.038	0.059	−0.009	0.001	−0.001	2,344

Notes: See equation (13) in Section II for the derivation of this more detailed labour productivity decomposition. Final two rows show the mean of changes over the two periods using all the annual observations shown above. Computations refer to revenue-weighted changes for the within sample of manufacturing firms.

sum up, the decline in demand appears to be the single most important determinant of the fall in UK labour productivity.

maximization) increases with both TFP-Q and demand. A fall in demand and/or TFP-Q thus pushes markups to decrease and this decrease in markups helps firms to contain the fall in both profits and revenue TFP.

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TABLE 5

Services. Changes of revenue TFP and its components over the period 2003–13

	Δ *TFP-R* (*WLD*)	Δω	Δμ	Δ *scale*	Δ *adjusted* ω	Δ *adjusted scale*	*Obs*
2004	0.004	0.154	0.011	0.044	0.070	−0.066	8,387
2005	−0.006	0.028	0.001	0.044	0.002	−0.007	7,813
2006	−0.001	−0.032	−0.005	0.044	0.038	−0.039	6,438
2007	0.008	0.258	0.019	0.042	0.101	−0.092	6,266
2008	−0.020	−0.185	−0.015	0.016	−0.090	0.070	5,674
2009	−0.002	0.042	0.005	−0.041	−0.011	0.010	6,493
2010	0.011	0.124	0.009	0.014	0.068	−0.057	6,079
2011	−0.000	−0.203	−0.018	0.017	−0.088	0.088	5,966
2012	0.017	0.141	0.009	0.022	0.073	−0.056	6,404
2013	−0.002	−0.066	−0.006	0.031	0.006	−0.008	6,626
2003–07	0.002	0.104	0.007	0.043	0.053	−0.052	28,904
2007–13	0.001	−0.021	−0.002	0.010	−0.005	0.006	37,242

Notes: The table shows mean revenue-weighted changes from $t-1$ to t, for the services firms within sample, of WLD revenue TFP as well as of the various MUOMEGA model components following from the linear revenue-TFP decomposition provided by equation (14) and applied to WLD revenue TFP. The final two rows show the mean of changes over the two periods using all the annual observations shown above.

Services

Using the within sample for services, and weighting observations by revenues, we report in Table 5 mean changes from $t-1$ to t in WLD revenue TFP and its components building on the decomposition of equation (14). For services, we find it best to use the year 2007 to define the pre- and post-crisis periods.

First, revenue TFP growth in services was rather weak already prior to the crisis with an average of 0.2 pp per year in the period 2003–07. This further weakened after the crisis, falling to 0.1 pp per year over 2007–13. In this respect, column 2 of Table 5 suggests (as for manufacturing) that a decline in the combined quantity TFP and demand component ω has been driving the weakening of TFP-R growth in services. At the same time, columns 3 and 4 indicate that this process has been accompanied by a decline in markups and production scale growth, which is again in line with the evidence provided above for manufacturing. Overall, this turned into a weakening of markup-adjusted ω (column 5) while the reduction in markups helped, as in manufacturing, to contain the fall in revenue TFP through the increase in markup-adjusted scale (column 6), with the two adjusted components adding up to the overall change in revenue TFP as from equation (14).

Figure 3 presents the results graphically and it is constructed in the same way as Figure 2 for manufacturing except that we now use 2007 to define the pre- and post-crisis periods. Panels (a) and (b) show quite neatly the break in revenue TFP and ω before and after 2007 while panels (c) and (d) highlight the decline in the evolution of markups and production scale. Panels (e) and (f) visualize the downturn in adjusted ω and the counter-increase in adjusted scale helping to contain the overall fall in TFP-R. Finally, Table A19 in Appendix S1 shows formal Chow test results confirming the presence of a structural break around 2007.

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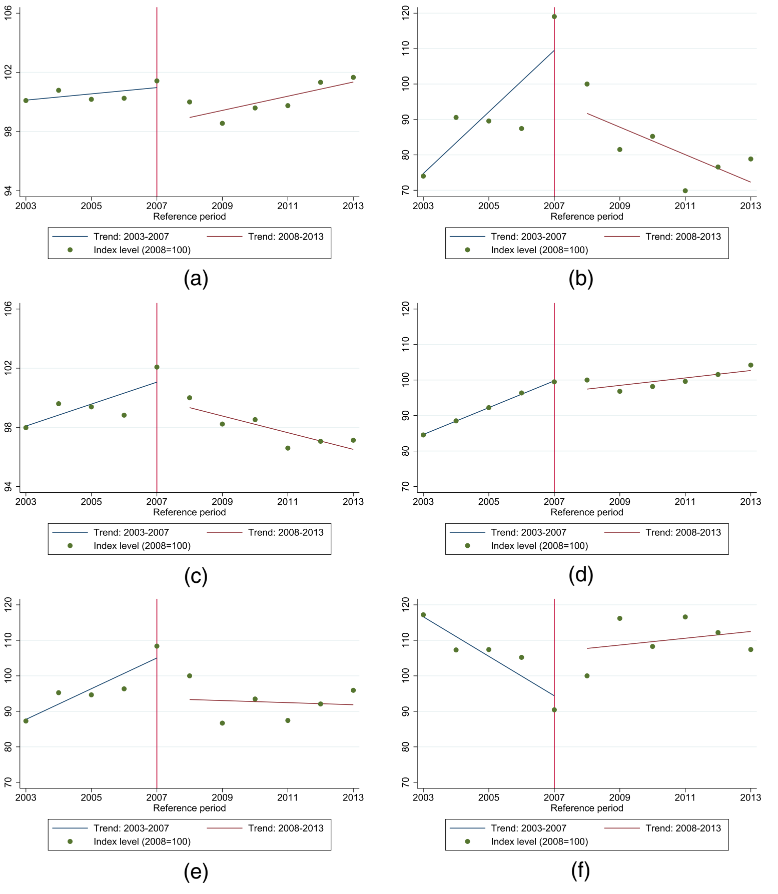

FIGURE 3. Services. Evolution of revenue TFP and its components over the period 2003–13. (a) WLD rev TFP; (b) ω; (c) μ; (d) scale; (e) adjusted ω; (f) adjusted scale. Index of revenue TFP (2008=100) calculated using revenue-weighted changes in mean annual value and measured using the WLD method (a) for the within sample of services firms. Panels (b)–(f) show indices of components of the WLD revenue TFP following from the decomposition (14) [Colour figure can be viewed at wileyonlinelibrary.com]

Table 6 shows the standard labour productivity decomposition over the period 2003–13 for our revenue-weighted services firms within sample.[26] Results indicate that services labour productivity growth in the period 2003–07 was about 0.8 pp a year and, while experiencing large drops in 2008 and 2009, decreased on average by 1.1 pp a year in the period 2007–13 ending up around 11.4 pp below its pre-crisis trend. Column 2 of Table 6 indicates that a key culprit of this under-performance is the drop in revenue TFP growth which declined from a positive 0.3 pp a year in the period 2003–07 to a negative −0.6 pp per year post-2007, i.e. $[(0.3 + 0.6)/(0.8 + 1.1)] = 47.4\%$ of the labour productivity

[26]As in the case of manufacturing we use, in our labour productivity decompositions, the (log) number of full-time-equivalent employees as a measure of the labour input and, in order to make sure that the decomposition goes through, we borrow our estimate of the output elasticity of labour, $\hat{\alpha}_L$, and recompute ω, TFP-R and scale accordingly. As can be appreciated from Table 6, this makes little difference in terms of the overall patterns of ω, TFP-R and scale so far discussed.

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TABLE 6

Services. Standard labour productivity decomposition (factor proportions version) over the period 2003–13

	$\Delta(r-l)$	Δ *TFP-R (WLD)*	$\gamma\Delta l$	$(\alpha_M)\Delta(m-l)$	$(\alpha_K)\Delta(k-l)$	*Obs*
2004	0.011	0.006	0.002	0.001	0.001	8,387
2005	0.004	−0.004	0.003	0.004	0.001	7,813
2006	0.007	−0.002	0.003	0.006	−0.001	6,438
2007	0.009	0.011	0.002	−0.005	0.001	6,266
2008	−0.049	−0.036	0.008	−0.021	−0.000	5,674
2009	−0.069	−0.024	−0.001	−0.043	−0.002	6,493
2010	0.039	0.017	−0.001	0.022	0.001	6,079
2011	−0.003	−0.009	−0.000	0.007	0.000	5,966
2012	0.011	0.013	−0.002	−0.000	0.000	6,404
2013	−0.002	−0.004	0.003	−0.001	0.000	6,626
2003–07	0.008	0.003	0.003	0.002	0.001	28,904
2007–13	−0.011	−0.006	0.001	−0.006	−0.000	37,242

Notes: See equation (11) in section II for the derivation of this standard labour productivity decomposition. Final two rows show the mean of changes over the two periods using all the annual observations shown above. Computations refer to revenue-weighted changes for the within sample of services firms.

growth slowdown.[27] The remaining share is almost entirely accounted for by a reduction of the log intermediates over labour ratio, i.e. the term $\Delta(m-l)$.

Table 7 provides further insights on the decline in labour productivity by highlighting the combined role of demand and TFP-Q as well as of markups. Markup-adjusted ω experienced a strong growth decline from the 6.5 pp per year average over 2003–07 to only 0.1 pp post-2007. At the same time, the related slowdown of markups has helped to contain the fall in labour productivity through a substantial improvement in the average yearly growth rate of the markup-adjusted labour term $\left(\Delta\left[\left(\frac{\gamma+1}{\mu}-1\right)l\right]\right)$ and intermediates over labour term $\left(\alpha_M\Delta\left(\frac{m-l}{\mu}\right)\right)$.[28] Finally, markup-adjusted capital over labour changes only weakly contributed throughout.

Comparing services with manufacturing

The evidence provided so far for manufacturing and services points to very similar patterns, although with somewhat different magnitudes, in terms of the common measures. More specifically, our results indicate that the labour productivity puzzle is to a large extent also a revenue TFP puzzle while the downturn in revenue TFP has been largely driven by a decline in the combined TFP-Q and demand component ω, to which firms have reacted by decreasing both markups and production scale. In turn, this decrease of markups

[27] Numbers for WLD revenue TFP in column 1 of Table 5 and column 2 of Table 6 are different because in the latter case we use, as indicated in a previous footnote, the number of employees rather than the wage bill as a measure of the labour input.

[28] As already highlighted above, markups are endogenous in the MULAMA/MUOMEGA models and their equilibrium level (determined by profit maximization) increases with ω. A fall in ω thus pushes markups to decrease and this decrease in markups helps firms to contain the fall in both profits and revenue TFP.

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TABLE 7

Services. More detailed labour productivity decomposition (factor proportions version) over the period 2003–13

	$\Delta(r-l)$	$\Delta(\omega/\mu)$	$\Delta\left[\left(\frac{\gamma+1}{\mu}-1\right)l\right]$	$\alpha_M\Delta\left(\frac{m-l}{\mu}\right)$	$\alpha_K\Delta\left(\frac{k-l}{\mu}\right)$	*Obs*
2004	0.011	0.062	−0.041	−0.011	0.000	8,387
2005	0.004	0.002	0.006	−0.004	0.001	7,813
2006	0.007	0.033	−0.020	−0.005	−0.001	6,438
2007	0.009	0.091	−0.059	−0.024	0.001	6,266
2008	−0.049	−0.092	0.051	−0.009	0.001	5,674
2009	−0.069	−0.031	0.006	−0.043	−0.002	6,493
2010	0.039	0.062	−0.033	0.009	0.001	6,079
2011	−0.003	−0.084	0.055	0.025	0.000	5,966
2012	0.011	0.065	−0.038	0.016	0.000	6,404
2013	−0.002	0.001	−0.002	−0.001	0.000	6,626
2003–07	0.008	0.047	−0.029	−0.011	0.000	28,904
2007–13	−0.011	−0.011	0.005	−0.006	0.000	37,242

Notes: See equation (15) in section II for the derivation of this more detailed labour productivity decomposition. Final two rows show the mean of changes over the two periods using all the annual observations shown above. Computations refer to revenue-weighted changes for the within sample of services firms.

and production scale has helped containing the negative impact of the less favourable post-crisis environment on TFP-R and so also on labour productivity.

In the case of manufacturing, our data allow us to go one step further and assess whether the reduction in ω has been TFP-Q and/or demand driven. The answer is that both a supply and a demand shock have negatively affected manufacturing revenue TFP. Our data cannot directly answer the above question for services. However we might conjecture, based on one key element, that supply (and possibly also demand) contributed to the overall downturn of services TFP-R. More specifically, we believe that the capital stock available to firms, which is generated by yearly investment, is the production input most closely related to the level of quantity TFP in the firm's production function. In this respect, Figure 4 shows the mean, across firms and revenue-weighted, annual level of real investment in the capital stock in manufacturing (left panel) and services (right panel) over 2004–13. The timing and depth of the decrease in investment and subsequent recovery are somewhat different between manufacturing and services but the overall picture is rather similar: a deep slump around the financial crisis and a sizeable (especially in manufacturing) recovery thereafter. Given that the fall in investment in manufacturing has turned into a sizeable post-crisis drop in TFP-Q, we can conjecture that a sizeable post-crisis drop in TFP-Q for services is also likely.

VI. Robustness

In what follows we provide evidence supporting the robustness of our results by using different samples, weighting schemes, estimation techniques, as well as a Translog production function.

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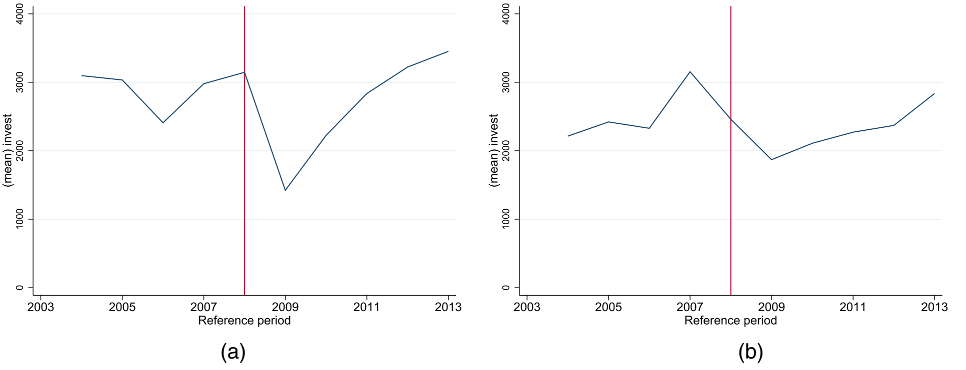

FIGURE 4. Investment patterns in manufacturing and services over the period 2004–13. (a) Manufacturing; (b) services. Mean firm annual real investment in the capital stock in manufacturing and services. Computations refer to the manufacturing and services within samples and are revenue-weighted [Colour figure can be viewed at wileyonlinelibrary.com]

Using the multi-product firm sample for manufacturing

In our main analysis for manufacturing we focus on single-product firms because dealing with multi-product firms requires a number of additional assumptions. However, multi-product firms account for a large share of production and revenue in manufacturing. In order to analyse multi-product firms we proceed as in FMMM and DGKP, i.e. we break them down into several single-product firms by using a procedure that allows firm-level inputs to be assigned to the different products produced by a multi-product firm (inputs assignment problem). In doing so, we then consider again within firm and product changes between $t-1$ and t to weigh observations based on the corresponding firm-product-specific revenue. Results displayed in Table A20 and Figure A1 indicate that our key insights apply to the sample of multi-product firms too.

Using unweighted or employment-weighted values

So far we have always considered firm revenue in order to weigh observations because we want our results to be representative of aggregate rather than average-firm outcomes. However, in Tables A21 and A22, and corresponding Figures A2 and A3, we provide results obtained using unweighted changes. As can be appreciated from the two tables and figures, our baseline results are virtually unaffected. At the same time, Tables A23 and A24, and corresponding Figures A4 and A5, show results obtained using firm employment to weigh observations and still confirm the robustness of our findings.

Using alternative estimation procedures

In our baseline results, we use the DGKP estimation procedure to estimate the production function and recover the different components of the MULAMA model for manufacturing, while for services we use the WLD estimation procedure to estimate the production function and recover the different components of the restricted MUOMEGA model. In order to assess the robustness of our results to the specific estimation technique employed

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we provide in Tables A25 and A26, as well as in Figures A6 and A7, results obtained using the FMMM estimation procedures for the MULAMA model (manufacturing) and MUOMEGA model (services). This new set of results is again in line with our baseline findings.

Using the Translog production function for manufacturing

The limited overlap between the Prodcom and ARDx data sets forces us to estimate a unique production function for manufacturing firms rather than estimate different production functions for different two-digit industries. In this respect, results provided in Table A27 and Figure A8, and obtained using the more flexible Translog production function, allay concerns about the issue of heterogeneity in output elasticities across firms and industries in manufacturing.

VII. Conclusions

In this paper we provide novel evidence that the poor productivity performance of UK firms post-2008 is due to a negative downturn in both quantity TFP and demand, pushing down sales, markups and revenue TFP, as well as labour productivity. More specifically, in the first part of our analysis, we focus on manufacturing firms and use information on firm-level prices and quantities to measure firm-level quantity TFP by building upon the frameworks developed in De Loecker *et al.* (2016) and Forlani *et al.* (2016). This allows us to further quantify firm-level demand and markups and, while aggregating-up the information at the manufacturing industry-level, compare the evolution of TFP-Q, markups and demand before and after 2008. Finally, we exploit two exact decompositions for TFP-R and labour productivity to show how changes in TFP-Q, markups and demand have affected the two productivity measures. Our results suggest that both slowing demand and a decline in quantity TFP, and the related markups fall, are behind the decline in revenue TFP and labour productivity in manufacturing. More specifically, the decline in quantity TFP is the main reason behind the decline in revenue TFP while the slowing down of demand is the key factor causing the decline in labour productivity.

In the second part of our analysis, we instead consider service industries and estimate a restricted version of the model due to the absence of reliable and meaningful information on prices. In doing so we find, for those measures that are common to both the full and restricted versions of the model, very similar patterns to those obtained for manufacturing. These findings, along with the absence of noticeable differences in capital investment patterns between manufacturing and services industries, lead us to conjecture that both supply and demand also contributed to the poor revenue TFP and labour productivity performance of UK service industries.

We believe that our results are important for at least two reasons. First, they are informative about the long-term impacts of the Great Recession. A fall in quantity TFP, due for example to slower technical progress, represents a permanent loss of productive potential with substantial long-term implications for the economy. By contrast a demand downturn, due for example to a general climate of uncertainty, could have less permanent consequences. Second, they are informative about the policies that could more effectively

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address the weak productivity outcomes of UK firms. In particular, our findings suggest that government policies should more prominently act towards boosting demand for firms rather than focusing only on productivity. In this respect, we believe this point might be particularly relevant in the recent Covid-19 crisis.

In terms of avenues for future research, we believe our analysis could be fruitfully extended to other countries to identify both common features and others that are country-specific. In this respect, the detailed price and quantity data used in our paper is available for quite a few countries including EU member states, the US and Brazil. At the same time, we believe the analysis could be usefully extended to a more recent time frame, possibly including the ongoing Covid-19 crisis, to provide evidence into the current patterns of, for example, TFP-Q, demand and markups.

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References

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

Andrews, D., Criscuolo, C., and Gal, P. N. (2015). *Frontier Firms, Technology Diffusion and Public Policy: Micro Evidence from OECD Countries*. OECD Productivity Working Papers, 2.

Atkeson, A. and Burstein, A. (2008). 'Pricing-to-market, trade costs, and international relative prices', *The American Economic Review*, Vol. 98, pp. 1998–2031.

Barnett, A., Chiu, A., Franklin, J., and Sebastiá-Barriel, M. (2014). The productivity puzzle: a firm-level investigation into employment behaviour and resource allocation over the crisis. *Bank of England Staff Working Papers*, 495.

Behrens, K., Mion, G., Murata, Y. and Südekum, J. (2014). 'Trade, wages, and productivity', *International Economic Review*, Vol. 55, pp. 1305–1348.

Bryson, A. and Forth, J. (2016). 'The UK's productivity puzzle', in Askenazy P., Bellman L., Bryson A., and Moreno Galbis E. (eds), *Productivity Puzzles Across Europe*, pp. 129–173. https://doi.org/10.1093/acprof:oso/9780198786160.003.0001

Cette, G., Fernald, J. and Mojon, B. (2016). 'The pre-great recession slowdown in productivity', *European Economic Review*, Vol. 88, pp. 3–20.

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

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

De Loecker, J. and Warzynski, F. (2012). 'Markups and firm-level export status', *American Economic Review*, Vol. 102, pp. 2437–2471.

Dhingra, S. and Morrow, J. (2019). 'Monopolistic competition and optimum product diversity under firm heterogeneity', *Journal of Political Economy*, Vol. 127, pp. 196–232.

Feenstra, R. C. (2003). 'A homothetic utility function for monopolistic competition models, without constant price elasticity', *Economics Letters*, Vol. 78, pp. 79–86.

Forlani, E., Martin, R., Mion, G., and Muûls, M. (2016). *Unraveling Firms: Demand, Productivity and Markups Heterogeneity*. CEPR Discussion Paper 11058.

Goodridge, P., Haskel, J. and Wallis, G. (2013). 'Can intangible investment explain the UK productivity puzzle?', *National Institute Economic Review*, Vol. 224, pp. 48–58.

Goodridge, P., Haskel, J. and Wallis, G. (2016). 'Accounting for the UK productivity puzzle: a decomposition and predictions', *Economica*, Vol. 85, pp. 581–605.

Grice, J. (2012). *The Productivity Conundrum, Interpreting the Recent Behaviour of the Economy*. Technical Report. Office for National Statistics.

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Hall, R. E. (1986). 'Market structure and macroeconomic fluctuations', *Brookings Papers on Economic Activity*, Vol. 2, pp. 285–338.
Haltiwanger, J., Kulick, R., and Syverson, C. (2018). *Misallocation Measures: The Distortion that Ate the Residual*. NBER Working Papers 24199, National Bureau of Economic Research, Inc.
Harris, R. and Drinkwater, S. (2000). 'UK plant and machinery capital stocks and plant closures', *Oxford Bulletin of Economics and Statistics*, Vol. 62, pp. 243–265.
Harris, R. and Moffat, J. (2017). 'The UK productivity puzzle, 2008 to 2012: evidence using plant-level estimates of total factor productivity', *Oxford Economic Papers*, Vol. 69, pp. 529–549.
Hottman, C. J., Redding, S. J. and Weinstein, D. E. (2016). 'Quantifying the sources of firm heterogeneity', *The Quarterly Journal of Economics*, Vol. 131, pp. 1291–1364.
Jacob, N. and Mion, G. (2020). *On the Productivity Advantage of Cities*, Mimeo, London, UK.
Martin, B. and Rowthorn, R. (2012). *Is the British Economy Supply Constrained II? A Renewed Critique of Productivity Pessimism*. Centre for Business Research, University of Cambridge.
McCann, P. (2018). *Productivity Perspectives Synthesis*. PIN Evidence Review 07, ESRC Productivity Insights Network.
OECD. (2018). *OECD Compendium of Productivity Indicators 2018*, OECD Publishing, Paris.
Office for National Statistics. (2007). *The ONS Productivity Handbook*, Palgrave-Macmillan, New York, NY.
Office for National Statistics (2018a). *International Comparisons of Productivity*. Technical Report.
Office for National Statistics. (2018b). 'Labour productivity, UK: October to December 2017', *Statistical Bulletin*. https://www.ons.gov.uk/employmentandlabourmarket/peopleinwork/labourproductivity/bulletins/labourproductivity/octobertodecember2017#:~:text=4.-,Output%20per%20hour%20up%20in%20both%20services%20and%20manufacturing,hours%20worked%20over%20the%20quarter
Office for National Statistics (2018c). *Products of the European Community, 1997-2016: Secure Access*. (8th Edition). [data collection].
Office for National Statistics. Virtual Microdata Laboratory, University of the West of England, Bristol (2017). *Annual Respondents Database X, 1998-2014: Secure Access* (4th Edition). [data collection].
Olley, G. S. and Pakes, A. (1996). 'The dynamics of productivity in the telecommunications equipment industry', *Econometrica*, Vol. 64, pp. 1263–1297.
Pessoa, J. P. and Van Reenen, J. (2014). 'The UK productivity and jobs puzzle: Does the answer lie in wage flexibility?', *Economic Journal*, Vol. 124, pp. 433–452.
Riley, R., Bondibene, C. R., and Young, G. (2013). *Productivity Dynamics in the Great Stagnation: Evidence from British Businesses*. CFM Discussion Papers 1407, Centre for Macroeconomics.
Riley, R., Rincon-Aznar, A., and Samek, L. (2018). *Below the Aggregate: A Sectoral Account of the UK Productivity Puzzle*. ESCoE Discussion Papers 2018-06, Economic Statistics Centre of Excellence.
Riley, R., Rosazza-Bondibene, C. and Young, G. (2014). 'The financial crisis, bank lending and UK productivity: sectoral and firm-level evidence', *National Institute Economic Review*, Vol. 228, pp. 17–34.
Schneider, P. (2018). *Decomposing Differences in Productivity Distributions*. Bank of England Working Papers 740, Bank of England.
Spence, M. (1976). 'Product selection, fixed costs, and monopolistic competition', *Review of Economic Studies*, Vol. 43, pp. 217–235.
Van Beveren, I., Bernard, A. B., and Vandenbussche, H. (2012). *Concording EU Trade and Production Data Over Time*. NBER Working Papers 18604, National Bureau of Economic Research, Inc.
Wooldridge, J. M. (2009). 'On estimating firm-level production functions using proxy variables to control for unobservables', *Economics Letters*, Vol. 104, pp. 112–114.
Zhelobodko, E., Kokovin, S., Parenti, M. and Thisse, J.-F. (2012). 'Monopolistic competition: Beyond the constant elasticity of substitution', *Econometrica*, Vol. 80, pp. 2765–2784.

Supporting Information

Additional Supporting Information may be found in the online version of this article:

Appendix S1. Supporting information

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