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Productivity Dispersion, Competition and Productivity Measurement*

Ralf Martin

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THE LONDON SCHOOL OF ECONOMICS AND POLITICAL SCIENCE

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Abstract
A startling fact of firm level productivity analysis is the large and persistent differences in both labour productivity and total factor productivity (TFP) between firms in narrowly defined sectoral classes. The competitiveness of an industry is potentially an important factor explaining this productivity dispersion. The degree of competition has also implications for the measurement of TFP at the firm level. This paper firstly develops a novel control function approach to production function and TFP estimation explicitly taking imperfect competition into account. This addresses a number of issues with the control function approach to productivity estimation. Secondly, applying this new approach to UK data it shows that productivity dispersion on average is about 50 percent higher than with standard TFP measures. It also shows that accounting for imperfect competition matters for estimates of the persistence of TFP. Thirdly, the paper finds a negative relationship between competition and productivity dispersion.

JEL classification: C81, D24, L11, L25
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Ralf Martin is a Research Economist with the Productivity and Innovation Programme at the Centre for Economic Performance, London School of Economics.

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"As we have examined this data we have been impressed by the diversity among plants and among industries." Baily et al. (1992)

1 Introduction

An intriguing feature of firm level productivity studies is the large and persistent differences in productivity between firms that operate in the same industry. For example Bartelsman and Doms (2000) find that top firms are at least twice as productive as bottom firms within narrow (4-digit) industrial classes surveying a wide range of studies. There is a long list of possible explanations for productivity dispersion.[1] These range from capital vintage effects, over learning and uncertainty to measurement error. Many of these explanations are in line with a Schumpeterian view[2] on the economy where there is a continuous process of entry, learning, selection and creative destruction. An alternative view is that productivity dispersion could be driven by lacking or imperfect competition in an industry; i.e. if competition is not very strong, then lagging firms which, otherwise would be forced to exit, continue to stay in the market thereby increasing productivity dispersion.

Interestingly, imperfect competition has not only - potentially - an impact on productivity dispersion, it also introduces biases and errors into conventional estimates of TFP (Klette and Griliches, 1996). Existing studies on productivity dispersion have not paid much attention to this kind of measurement problem.[3]

In this paper I make three contributions: Firstly, I develop a novel control function approach to TFP estimation that explicitly takes imperfect competition into account. This approach also addresses a number of concerns with existing control function approaches, such as identifiability (Ackerberg et al., 2007; Bond and Söderbom, 2005) or the plausibility of investment as a proxy for un-observed heterogeneity(Levinsohn and Petrin, 2003; Griliches and Mairesse, 1995). I compare this new approach to alternative approaches, using both, actual data for the UK and artificial Monte Carlo data. I find that it provides more precise estimates and is more robust to a number of misspecification issues than other approaches.[4]

Secondly, I use this approach to examine productivity dispersion across UK industries. I find that accounting for imperfect competition matters for the measurement of productivity dispersion. Correctly measured dispersion is on average 50 percent higher than using standard TFP estimates. It also affects the persistence of TFP over time. High persistence of firm level TFP is an important stylised fact in the analysis of productivity dispersion. If productivity dispersion is primarily driven by Schumpeterian selection, we would expect that TFP is *not* very persistent and firms at the bottom of the productivity distribution either exit or move up in the distribution. I find that correctly measuring TFP leads to dispersion estimates that are much more in line with this latter kind of explanation for productivity dispersion; i.e. compared to standard TFP estimates, persistence becomes weaker at the bottom and stronger at the top of the productivity distribution.

Thirdly, I examine if there is a link between dispersion and competition. Using a measure of

[1]Baily et al. (1992) and Bartelsman and Doms (2000) provide comprehensive discussions.

[2]See Aghion and Howitt (1998) Chapter 2 for a discussion

[3]e.g. Baily et al. (1992), Bartelsman and Dhrymes (1998) and Syverson (2004) all rely on TFP estimates that assume perfect competition and constant returns to scale.

[4]The framework I am proposing is available as an easy to use STATA programme under http://www.mondpanther.org/pubtwik/bin/view/MP/TrueMethod.

competition derived from the estimation approach developed in this paper, I find a significantly negative correlation between competition and productivity dispersion.
The reminder of this paper is organised as follows: Section 2 develops the new estimation framework formally. Section 3 discusses the dataset I am using which is the Annual Respondents Survey (ARD) provided by the UK Office of National Statistics (ONS).[5] Section 4 reports dispersion estimates based on the new productivity measure and discusses how they compare to dispersion estimates based on traditional productivity measures. Section 5, looks at the dynamic characteristics of the new productivity measure as well as the link between productivity dispersion and the competitiveness of an industry. Section 6 concludes.

2 A framework to estimate firm level TFP

Standard productivity analysis normally starts by assuming a production function; i.e. a mapping from input quantities to output quantities. In order to identify its coefficients on the basis of that assumption alone we require data on these quantities. Unfortunately this is rarely available at the firm or plant[6] level. Most business level datasets only contain data on revenues and - with the exception of labour - expenditure on various inputs. In order to proceed despite these data deficiencies, it is common practice to assume perfect competition in product markets. As a consequence output prices should be equal across businesses in a sector and revenues deflated with a sectoral price index become indexes of relative output quantities. Similarly, an assumption on equal factor prices across firms ensures that factor expenditure can be used as an index for factor quantities.[7] In the following I relax the assumption on perfect competition in product markets. Ideally we would like to have a framework which relaxes both assumptions. Eslava et al. (2005) using Columbian data is one few studies having both, detailed input and output prices. They find that ignoring variation in input prices has only a minor effect on resulting TFP estimates whereas the effect of ignoring output prices is large. This justifies focusing on output prices first.[8]

Starting with what we actually observe at the plant level in absence of plant level prices[9], we can write revenue as

$$r_{it} - p_t = q_{it} + p_{it} - p_t \tag{1}$$

where all variables are in terms of log deviations from the industry median firm in terms of revenue per worker. Thus, r_{it} is the deviation of revenue[10] from the revenue of the median

[5]Access to this data is restricted. However, researchers with access to the UK Office of National Statistics Datalab find all data to reproduce the results on the standard data lab server under t:/ceriba/spreadpublish/.

[6]Below I apply my framework to plant level data. However this general discussion applies for both firms and plants. I will therefore use the terms interchangeably.

[7]Note that while perfect competition in factor markets would be a sufficient condition for equal factor prices it is not necessary.

[8]Ignoring output prices only leads to correlation coefficient of 0.66 with the "perfect" TFP measure accounting for both input and output prices. Ignoring input prices only, leads to a correlation coefficient of 0.98

[9]Here I follow Klette and Griliches (1996)

[10]Quantity produced in a given year at a given plant times price. Because plants might have inventories, reported revenue might not exactly refer to quantities produced in a given year. Theoretically this offers firms another choice variable which could be considered in our model of the firm. For the time being I am abstracting from this however and simply use a revenue measure that is adjusted for inventory changes. See also the discussion in the data section 3

plant; i.e. $r_{it} = \log R_{it} - \log R_{Median,t}$, p_{it} is the plant level output price, p_i is a sectoral price index and q_{it} the output quantity. Writing and estimating the model in terms of deviations from the median is sufficient given our focus on productivity dispersion. It is a very convenient technique because it allows a log linear representation of a flexible form production function as will become clear below. It also implies that we can ignore all terms which are constant across all firms in an industry at a given point in time. This means that the industry price index, for example, becomes $p_t = 0$.

To proceed we must introduce assumptions regarding technology and market structure. For the production function assume that it is of a general form but homogenous of degree γ, i.e.

$$Q_{it} = A_{it} \left[f(\mathbf{X}_{it}) \right]^{\gamma} \tag{2}$$

where $f(\cdot)$ is a general differentiable linear homogenous function[11], A_{it} is a Hicks neutral shift parameter[12] and $\mathbf{X}_{it}$ is a vector of factor inputs. Avoiding any further assumptions on the form[13] of the production function we can invoke the mean value theorem to write a plants output relative to the median plant as

$$q_{it} = a_{it} + \sum_x \alpha_x x_{it} \tag{3}$$

where

$$\alpha_x = \gamma f_x(\bar{\mathbf{X}}_{it}) \frac{\bar{X}_{it}}{f(\bar{\mathbf{X}}_{it})} \tag{4}$$

$f_x(\cdot)$ denotes the partial derivative of $f(\cdot)$ with respect to factor x, $\bar{\mathbf{X}}_{it}$ is some point in the convex hull spanned by $\mathbf{X}_{it}$ and $\mathbf{X}_{Median,t}$ and all input variables and output quantity are in terms of deviations from the median plant.[14]

For the market structure I follow Klette and Griliches and assume a Dixit-Stiglitz monopolistic competition setting; i.e. assuming a utility function for goods from a particular sector

$$U_t = \left[\sum_i (\Lambda_{it} Q_{it})^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}} \tag{5}$$

plant level demand becomes

$$Q_{it} = \frac{R_t}{P_t} \Lambda_{it}^{\eta-1} \left(\frac{P_{it}}{P_t} \right)^{-\eta} \tag{6}$$

where R_t is the sectoral revenue, P_t the sectoral price index and P_{it} the price of the individual firm. Λ_{it} is a shift parameter which captures differences across plants in product characteristics such as quality or simply consumer valuation.

A key assumption implied by 6 is that the elasticity of demand η is constant across plants. This is quite restrictive for a number of reasons. It might well be possible that different plants

[11]All estimations reported later are calculated for each 3 digit industry separately. Thus, the production function and – unless specified differently – all other parameters are constant within each industry but free to vary between industries. To avoid notational clutter I abstain from using industry indices.

[12]Also known as TFP.

[13]Except for differentiability that is.

[14]This transformation has been used in a similar way by Klette (1999) and Baily et al. (1992).

face different demand elasticities [15] In the appendix I discuss how my framework might be extended to allow for varying markups. This is an issue for some additional research and for the time being I maintain this assumption despite its caveats. Section 2.4 has further discussion on how it might affect my results.

With or without varying markups, profit maximization under demand function 6 implies a markup pricing rule

$$P_{it}\gamma\frac{Q_{it}}{f(\mathbf{X}_{it})}f_x(\mathbf{X}_{it}) = \mu W_{zit} \tag{7}$$

i.e. prices must be such that the marginal value product is μ times the marginal cost of each factor, where $\mu = \frac{1}{1-\frac{1}{\eta}}$.

As pointed out by Klette (1999), equation 7 can only be expected to hold for production factors which are easily adjustable. I distinguish in the following between 3 types of inputs: labour, intermediates and capital. I assume that labour and material can be adjusted immediately to their optimal value while capital is fixed in the short term.[16] As a consequence equation 7 holds for labour L and intermediates M, conditional on the level of the capital stock K. For intermediates and labour we can therefore write

$$\alpha_j = \mu\frac{W_{xt}X_{it}}{P_{it}Q_{it}} = \mu s_{xit} \tag{8}$$

where s_{xit} is the revenue share of factor X. Further because we assumed linear homogeneity of $f(\cdot)$

$$\alpha_K = \gamma - \alpha_L - \alpha_M \tag{9}$$

We have that

$$q_{it} = a_{it} + \mu vi_{it} + \mu\varsigma_{it} + \gamma k_{it} \tag{10}$$

where

$$vi_{it} = \sum_{x\neq k}\bar{s}_{xit}(x_{it} - k_{it}) \tag{11}$$

is an index of factor usage and ς_{it} is an iid error introduced by the fact that the first order conditions might not hold exactly. Theoretically – as a consequence of the invocation of the mean value theorem in equation 3 – $\bar{s}_{xit}$ is the factor share which prevails at some point in the convex hull spanned by $\mathbf{X}_{it}$ and $\mathbf{X}_{Median,t}$. If we are willing to follow common practice in productivity analysis[17] and approximate this implied factor share by the average factor share at plant i and the share at the median plant – i.e.

$$\bar{s}_{xit} \approx \frac{s_{it} + s_{Median,t}}{2} \tag{12}$$

– then vi_{it} can be directly calculated from the data without estimation.

[15] Katayama et al. (2003) are the only study to the best of my knowledge, that go beyond constant markups in a productivity context, however - as discussed in more detail later - at the cost of restrictive assumptions on the shape of the production function.

[16] It is no problem to have additional fixed factors. It would however impose some additional restrictions on the shape of the production function. For comparability with the related approaches by Levinsohn and Petrin (2003) and Olley and Pakes (1996) I stick with the current assumption for the time being.

[17] see for example Baily et al. (1992).

Using a logged version of the demand function 6 to get rid of the plant level price, p_{it} in equation 1 yields[18]

$$r_{it} = \frac{1}{\mu} q_{it} + \frac{1}{\mu} \lambda_{it} \tag{13}$$

Combining that with equation 10 results in

$$r_{it} - vi_{it} = \frac{\gamma}{\mu} k_{it} + \omega_{it} + \varsigma_{it} \tag{14}$$

where

$$\omega_{it} = \frac{1}{\mu}(a_{it} + \lambda_{it}) \tag{15}$$

Equation 14 is essentially an extension of standard factor share methods to a situation of imperfect competition and non constant returns to scale. We can use it to make explicit what we actually measure when using standard TFP methods in such a situation. Measured TFP (MTFP) then becomes

$$MTFP_{it} = \left(\frac{\gamma}{\mu} - 1\right) k_{it} + \omega_{it} + \varsigma_{it} \tag{16}$$

i.e. while standard TFP tries to measure a_{it} what we actually obtain is a composite of technical efficiency, a_{it}, the demand shock λ_{it} and a factor involving capital. Is there any hope of recovering a_{it}? It will be difficult without plant level prices. However, do we really want to estimate a_{it}? This depends of course to some extent on the research objective in mind. However, generally economists are interested in TFP because – at least implicitly – they want to assess the relative welfare contributions of different plants. It turns out that under the current model ω_{it} is the correct measure to seek. To see this more clearly note that given the welfare function in equation 5 (the log median deviation of) the welfare contribution of a particular plant i is $\lambda_{it} + q_{it}$. Now we can undertake the thought experiment of examining what this welfare contribution would be if the resources used to operate plant i were used in conjunction with the entrepreneurial skills and technical efficiency prevailing at some other plant, 0 say. Thus holding the input vector fixed we get a welfare contribution of

$$\lambda_{0t} + a_{0t} + \gamma log f(\mathbf{X_{it}}) \tag{17}$$

Or put differently, $\lambda_{it} + a_{it}$ – and with constant markups in turn ω_{it} – indexes the welfare contribution of plants conditional on their factor inputs. The difference between firm i and 0 in ω is thus an index of the marginal impact of having firm i rather than firm 0. In the reminder I will refer to the composite of demand and technical shock ω as *Total Factor Value Productivity* (TFVP).

To get an estimate of ω_{it} under constant markups μ across firms all that is needed is an estimate of $\frac{\gamma}{\mu}$. In principle this could be obtained by a regression of $r_{it} - vi_{it}$ on capital. However, the concern is that such a regression would be biased because of two kinds of endogeneity problems. Firstly, there might be a correlation between the unobserved shocks ω_{it} and the input variables vi_{it} and k_{it}. This is the classical production function endogeneity problem[19]. Secondly, in plant level data, endogeneity is introduced through a correlation between the exit decision of plants and the observed explanatory variables. In the next two sections I will develop a modification of the framework suggested by Olley and Pakes (1996)(OP) in order to address these issues.

[18]Recall that all aggregate variables such as P_t and R_t vanish if we write the system in terms of deviations from the median

[19]see Griliches and Mairesse (1995)

2.1 How to account for endogeneity

Formally the endogeneity problem follows from the profit maximisation problem of plants. If plants maximise profits conditional on the state variables capital k_{it} and plant specific demand and TFP shock composite, ω_{it}, then the variable factors are functions of k_{it} and ω_{it} as well as factor costs and various aggregate variables which form the information set of plants about the future. I follow OP in assuming that factor costs are uniform across plants. Formally we can write:[20] $l_{it} = l(k_{it}, \omega_{it})$ and $m_{it} = m(k_{it}, \omega_{it})$. Equally the firms short term net revenue function – i.e. revenue minus variable costs – is a function of ω_{it} and capital:

$$\Pi_{it} = R_{it} - C_{it} = \Pi(\omega_{it}, k_{it}) \tag{18}$$

In the appendix A I show that under the assumptions made so far about market structure and production technology, this function is monotone in ω_{it}. This implies that we can invert it and write

$$\omega_{it} = \phi_{\omega}(\Pi_{it}, k_{it}) \tag{19}$$

where $\phi_{\omega}(\cdot) = \Pi^{-1}(\cdot)$. Consequently, we can use net revenues in a similar way as OP have used investment and Levinsohn and Petrin (2003) (LP in what follows) materials to control for ω_{it} in order to estimate equation 14. The following further steps are needed for that purpose. Start by assuming that ω_{it} evolves as a Markov process:

$$\omega_{it} = E\{\omega_{it}|\omega_{it-1}\} + \nu_{it} \tag{20}$$

where ν_{it} is iid. Consequently our regression equation 14 can be rewritten as

$$r_{it} - vi_{it} = \frac{\gamma}{\mu} k_{it} + E\{\omega_{it}|\omega_{it-1}\} + \nu_{it} + \varsigma_{it} \tag{21}$$

If we can assume that k_{it} is only correlated with the expected component of ω_{it} but not with ν_{it} then it is sufficient to control for $E\{\omega_{it}|\omega_{it-1}\}$ in order to estimate $\frac{\gamma}{\mu}$ consistently. OP get this condition by assuming that investment in t only affects the capital stock in $t+1$. An alternative assumptions – which OP cannot make because they use investment in t to predict ω_{it} – is that investment in t is predetermined in period t.

But how should we control for $E\{\omega_{it}|\omega_{it-1}\}$? We do not know which functional form $E\{\omega_{it}|\cdot\}$ takes, but we have found in equation 19 a way to express its argument as a function of observables. We can therefore rewrite equation 14 as

$$r_{it} - vi_{it} = \frac{\gamma}{\mu} k_{it} + g(k_{it-1}, \Pi_{it-1}) + \nu_{it} + \varsigma_{it} \tag{22}$$

where $g(\cdot) = E\{\omega_{it}|\phi\omega(\cdot)\}$. If are willing to approximate $g(\cdot)$ by a higher order polynomial 22 reduces to a simple least squares problem. Alternatively we could use equation 22 to get initial values for a more challenging but more efficient – in the econometric sense – procedure: Start with a first stage nonparametric regression

$$r_{it} - vi_{it} = \phi(k_{it}, \Pi_{it}) + \varsigma_{it} \tag{23}$$

[20] For conciseness I only focus on what actually varies at the plant level; e.g. employment might also depend on the wage level, the business cycle, etc. However to the extent that these things do not vary across firms in a sector all this cancels out because of the analysis in relative terms.

where $\phi(k_{it}, \Pi_{it}) = \frac{\gamma}{\mu}k_{it} + \phi_\omega(\Pi_{it}, k_{it})$ because as long as we do not know the functional form of $\phi_\omega(\cdot)$ we cannot identify $\frac{\gamma}{\mu}$ separately in such a regression. This provides an estimate of $\hat{\phi}_{it}$ for each observation. Equation 22 can then be restated as a nonlinear least squares problem:

$$r_{it} - vi_{it} = \frac{\gamma}{\mu}k_{it} + h(\hat{\phi}_{it} - \frac{\gamma}{\mu}k_{it-1}) + \nu_{it} + \varsigma_{it} \tag{24}$$

where $h(\cdot) = E\{\omega_{it}|\cdot\}$ is approximated again by a polynomial.

2.2 Accounting for exit

The fact that input factors are functions of ω_{it} is not the only factor that leads to endogeneity in regressions of equation 14. Because plants can exit the industry or die all together there is an additional endogeneity problem from a dependance of this exit decision on the current level of the capital stock. Ericson and Pakes (1995) provide an elaborate model that formalises this idea. What is required intuitively is that the scrap value upon exiting increases more slowly than profits upon continuation, with increasing capital stock. For the empirical application it suffices to note that there is some lower threshold level of ω that is a function of k_{it}

$$\underline{\omega}_{it} = \underline{\omega}_{it}(k_{it}) \tag{25}$$

If a plant i's level of ω_{it} drops below $\underline{\omega}_{it}$ it exits. Consequently our regression equation 21 becomes

$$r_{it} - vi_{it} = \frac{\gamma}{\mu}k_{it} + E\{\omega_{it}|\omega_{it-1}, \underline{\omega}_{it}\} + \nu_{it} + \varsigma_{it} \tag{26}$$

Thus to run this equation we need some form to control for $\underline{\omega}_{it}$ as well as for ω_{it}. I follow Olley and Pakes (1996) and apply one of their derivations to my framework. Note that for the probability that a plant stays in the market:

$$\begin{aligned} P(\text{Stay after period t}) &= P(\omega_{it} > \underline{\omega}_{it+1}(k_{it+1})|\underline{\omega}_{it}(k_{it}), \omega_{it}) \\ &= p(\underline{\omega}_{it}(k_{it}), \omega_{it}) \\ &= p(k_{it}, \Pi_{it}) = P_{it} \end{aligned} \tag{27}$$

where the third equality follows from equation 19. Thus we can a run a Probit on continuation with capital and profits as explanatory variables. This gives an estimate of P_{it}. Now if P_{it}, the probability that a plant stays in the market, increases monotonically with $\underline{\omega}_{it}$, $p(\cdot)$ is invertible, and we can write

$$\underline{\omega}_{it} = p^{-1}(P_{it}, k_{it}, \Pi_{it}) \tag{28}$$

This means that we can control for $\underline{\omega}_{it}$ using the estimate of P_{it}. Consequently, equation 22 becomes

$$r_{it} - vi_{it} = \frac{\gamma}{\mu}k_{it} + g(\Pi_{it-1}, k_{it-1}, \hat{P}_{it-1}) + \tilde{\nu}_{it} + \varepsilon_{it} \tag{29}$$

and we can proceed as outlined in the last section.

2.3 The measurement error problem

Another issue with productivity dispersion arises from measurement error in input factor variables. Specifically with the UK data I am using a concern is the labour input variable which is a headcount measure of the people employed without any correction for different skill levels. This is the only employment measure which is consistently available over the time period studied. However, the control function approach outlined can easily be extended to account for this under the assumption that similarly skilled people are paid the same wage across firms and the production function is separable in labour.[21] The argument is as follows: under the assumptions of the control function approach effective labour input is a function of $\omega_i t$ and capital which in turn implies that it is a function of the control variable - $\pi_i t$ in our case - and capital. Thus we can write observed labour input as

$$\tilde{l}_{it} = \phi_L(\Pi_{it}, k_{it}) + \varrho^L_{it} \tag{30}$$

where ϱ^L_{it} is a measurement error. Approximating $\phi_L(\Pi_{it}, k_{it})$ by a polynomial we can run a preliminary regression to get an estimate of effective labour

$$\hat{l}_{it} = \hat{\phi}_L(\Pi_{it}, k_{it}) \tag{31}$$

This can be used to calculate the variable factor index.

$$\hat{vi}_{it} = \sum_{z \neq K} \bar{s}_j(\hat{x}_{zit} - k_{it}) \tag{32}$$

Next we can proceed as described in Section 2.1 to get an estimate of $\frac{\gamma}{\mu}$ and $\phi(\cdot)$. Eventually we can compute the corrected estimate of ω_{it} as

$$\hat{\omega}_{it} = \hat{\phi}(\Pi_{it}, k_{it}) - \widehat{\left(\frac{\gamma}{\mu}\right)} k_{it} \tag{33}$$

An estimate of TFVP *affected* by measurement error we can get as

$$\hat{\tilde{\omega}}_{it} = \tilde{vi}_{it} - \widehat{\left(\frac{\gamma}{\mu}\right)} k_{it} - \hat{\varsigma}_{it} \tag{34}$$

where $\hat{\varsigma}_{it}$ is derived from the first stage regression in equation 23. Note that this procedure is similar to but more general than the common practice of accounting for skill by including average wage as an additional explanatory variable in a production function regression.

2.4 Discussion

This section contains further discussion of the assumptions of the framework introduced in the previous sections and compares it with other TFP estimation frameworks.

[21] i.e. the impact of the different skill types on output can be captured by single index composite function capturing the joint effective labour input of the different skill types. Formally $Q_{it} = Q(\mathbf{X}_{it}, \Xi(\mathbf{V_{it}}))$ where $\mathbf{X}_{it}$ is a vector with all production factors apart from labour, $\mathbf{V_{it}}$ is a vector of all skill types and $\Xi(\cdot)$ is differentiable function.

Standard TFP Equation 16 showed what the standard factor share based TFP measure captures if the assumptions of the new framework hold. Is there any prior expectation about how dispersion measures derived from the new framework and standard TFP compare? Recall from equation 16, that the difference between the standard measure and the new TFVP is captured by the capital stock term

$$\left(\frac{\gamma}{\mu} - 1\right) \tag{35}$$

Notice that $\frac{\gamma}{\mu}$ is the elasticity of revenue with respect to an increase in the factor index $f(\mathbf{X}_{it})$.[22] This elasticity is positive because more inputs always means more revenue. The elasticity is higher, the higher the returns to scale, but it is lower the higher the markup. This is because with a lower demand elasticity (higher markup) the plant has to reduce prices more in order to sell all the additional output from the increased factor input. The standard TFP measure ignores this revenue reducing aspect and therefore assigns too high a weight to capital.[23] Consequently, if there is a positive correlation between ω and capital[24] then standard TFP underestimates TFVP for high productivity plants.

Varying markups How would estimates of ω and productivity dispersion be affected if – contrary to my current assumption – markups vary between different plants? A somewhat counterintuitive result that emerges is that plants with higher markups (lower η) would – all else equal – have lower measured ω. Why is this the case? The argument is very similar to the discussion in the last paragraph. If plants have different markups μ_i but we nevertheless impose a regression model such as equation 14, then the resulting parameter estimate we get for $\beta_K = \frac{\gamma}{\mu}$ is likely to be too high for high markup plants:[25]

$$\frac{\gamma}{\mu} > \frac{\gamma}{\mu_i} \tag{36}$$

Again the intuition is that a marginal increase in capital would have a smaller impact on revenue because the price drop required to clear markets would have to be larger. Hence again we would attribute too much of the revenue variation to capital for high markup plants. This effect would be reinforced if higher markups are correlated with higher capital stocks. Also, if variations in markup are positively correlated with variations in consumer valuation λ, then for plants with high λ measured values of TFVP would tend to underestimate true TFVP and vice versa for low λ plants. As a consequence dispersion estimates would be too low. Is there a way to account for varying markups at the plant level? [26]Appendix C suggests an extension of

[22]To see this note that $r_{it} = q_{it} + p_{it} = \frac{1}{\mu} q_{it} + OtherExogenousFactors_{it}$. Because $q_{it} = a_{it} + \gamma \ln f_{it}$ we get $\frac{\partial r_{it}}{\partial \ln f_{it}} = \frac{\partial [\frac{\gamma}{\mu} \ln f_{it}]}{\partial \ln f_{it}}$.

[23]Notice that this follows from expression 35 because we must have that $\frac{\gamma}{\mu} < 1$. This is a requirement for the existence of a long run equilibrium (after capital has fully adjusted) with positive production. If the scale parameter is too high the required price drop would shrink revenues so fast that the firm could never achieve positive profits. A formal prove of this is in appendix B

[24]i.e. better plants also invest more

[25]While the estimate would be bound by the most extreme coefficient values in the sample there is not guarantee that it would be a consistent estimate of the average coefficient value. Compare the discussion in Dumouchel and Duncan (1983)

[26]**?** develop a test of constant markups across firms which can help deciding if such an extension is necessary in specific cases.

the estimation framework introduced in this paper to do precisely that. The key idea is to use a control function approach using both net revenues and the factor share of a variable factor as arguments of the control function.

Differences to other control function approaches What are the differences of the approach introduced in this study compared (M-approach) to other control function approaches? Three points are worth pointing out: Firstly, the M approach does not suffer from the identification problems discussed by both Ackerberg et al. (2007) (ACF) and Bond and Söderbom (2005) (BS). Their criticism is as follows: both OP and LP have to assume that variable inputs are functions of ω_{it} and k_{it} only. If this was not the case, then those variables would enter as additional state variables in the control function. However when the assumption is true e.g. OP can derive the following first stage regression equation:

$$r_{it} = \beta_L l(\omega_{it}, k_{it}) + \beta_M m(\omega_{it}, k_{it}) + \phi(i_{it}, k_{it}) + \varsigma_{it} \tag{37}$$

OP suggest that this equation can be used to estimate β_L and β_M. Writing the equation as in 37, however, makes it clear that such a regression would suffer from a multi-colinearity problem because all variable production factors are driven by the same variation and are therefore perfectly correlated. Thus, the fact that in practice many studies were able to estimate versions of equation 37 probably implies that these models were misspecified for the data at hand. The M-approach avoids this issue by not estimating the coefficients on variable factors at all but rather using the factor share approach.

Secondly, consider the implications of using net revenue π_{it} as a proxy for unobserved heterogeneity. As with using materials[27] it addresses one of the major criticisms of the OP approach. Among others Griliches and Mairesse (1995) expressed concern that investment might only react to the longer term components of the unobserved heterogeneity. Formally, OP manage to get the required results by their particular assumptions on the dynamics of investment and TFP. Given their assumptions, investment in t is a function of expected TFP:

$$i_{it} = \iota(E_t\{\omega_{t+1}\}) \tag{38}$$

Thus investment only becomes a function of ω_t today under the Markov assumption 20, which ensures that the complete shock in t feeds into the expectation of ω_{it} in $t+1$. Consequently, OP's framework would not work with a simple shock process such as

$$\omega_{it} = \mu + \nu_{it} \tag{39}$$

where ν_{it} represents an iid process. Because $E_t\omega_{it+1} = \mu$, i_{it} would be a poor index of ω_{it}. Note that although I also made assumption 20 it is not generic to my framework. I use it to mimic OP but if necessary I could just as well accommodate assumptions such as 39. While the exact type of shock process might be debatable there is another problem with investment as shock process that is clearly of empirical relevance. Even allowing all assumptions of OP the monotonicity between ω_{it} and i_{it} breaks down if adjustment costs are non-convex and firms might simply not react to all shocks in the short term.

Relative to LP who use material or energy inputs as proxy using net revenues offers the following advantage: to have monotonicity between material input and ω_{it}, LP show that a

[27] As LP do.

condition on the cross derivative of labour and materials must hold. The intuition for this is that labour and materials should be complements. If they are substitutes we might have a situation in which a higher ω leads to higher labour usage but lower material usage because some of the material input is substituted by labour. While this is not an implausible condition, using net revenues instead does not require any such condition at all. In a Monte Carlo Study in the appendix I further find that using net revenue, rather than materials makes the control function approach less sensitive to misspecification; i.e. if the variable factors - labour and materials - are not fully flexible, then the production function estimates become bias. However the bias is less severe when using net revenue as compared to using materials as proxy.

Fourth and finally, what is the difference compared to the suggestions of ACF and BS to address the identification problem discussed as point 2? ACF assume that labour is not variable but continue with the control function approach whereas BS assume that all production factors adjust slowly and devise an approach that rests solely on lagged input factors as instruments. More formally, ACF end up with the following stage 2 equation

$$r_{it} = \beta_L l_{it} + \beta_M m_{it} + \beta_K k_{it} + g(\hat{\phi}(m_{it-1}, k_{it-1}) - \beta_L l_{it-1} - \beta_M m_{it-1} - \beta_K k_{it-1}) + \nu_{it} + \varsigma_{it} \quad (40)$$

which is identified from the nonlinear restrictions and zero moment conditions between lagged input factors and ν_{it} as well as a zero moment condition between k_{it} and ν_{it}. BS on the other hand, assuming zero variation in ς_{it} and a linear form for $g(\cdot)$ end up with the following equation:

$$r_{it} = \beta_L l_{it} + \beta_M m_{it} + \beta_K k_{it} + \rho(r_{it-1} - \beta_L l_{it-1} - \beta_M m_{it-1} - \beta_K k_{it-1}) + \nu_{it} \quad (41)$$

which again they identify from zero moment conditions in lagged variables. Both of these equations raise a number of issues. Firstly, identification: Equation 40 is identified as represented above.[28] However suppose we have several material input factors which adjust without delay; e.g. different types of intermediates. Then 40 suffers from similar collinearity problems as those encountered in equation 37. Further, even if there is only one variable factor - (materials as above), identification - while theoretically established - is difficult in practice because the nonlinear moment conditions have several local solutions. One strategy adopted for example by ACF to avoid these problems is to analyse the production function in terms of value added; Note however, that this imposes a Cobb-Douglas production function as we implicitly require that all firms have the same factor shares.[29] While identification is difficult if material inputs do not vary, both approaches will fail or be numerically challenging if there is not sufficient independent variation in labour inputs. Secondly, biases: BS assume that material inputs adjust with delay. If this is the case then all the control function approaches based on material inputs are misspecified and potentially biased. In addition, the LP, OP and M approach might all be biased if labour is not sufficiently flexible. The BS framework is subject to biases on the other hand if the ς_{it}-shock term matters. Further it assumes a linear AR dynamic process in TFP. Thirdly, efficiency: irrespective of biases, because the different approaches require estimation of different numbers of parameters and impose not only different but also different numbers of restrictions, the precision of the resulting estimates might vary considerably. In summary,

[28] A more detailed discussion on this can be obtained from the author on request.

[29] Although related, the issue is somewhat different from the concerns in the macro literature discussed for example by Basu and Fernald (1997). They are looking at a divisia index of value added growth; i.e. the differential between two points in time. In that case more general production functions that are separable in materials can be approximated using a value added approach.

none of the approaches is perfect under all circumstances. Which approach is the most appropriate depends on which assumptions apply in particular cases. Another issue is that even if some assumptions do not apply it might not matter too much for the actual estimates of the production function parameters. In appendix D I will shed some light on this last issue by providing Monte Carlo Evidence on the different frameworks. This shows that the M approach suffers from modest biases even if the assumption of perfectly flexible material inputs or labour inputs is strongly violated. Because it requires estimation of fewer parameters the M approach provides estimates with vastly lower standard errors. Any biases that might arise are therefore well within the range of the much wider confidence intervals of most other approaches.

Relation to other production function estimation approaches The idea of solving the production function endogeneity problem by way of control functions described above is a rather late addition to applied econometric methodology. Most earlier approaches relied on implementations of dynamic panel data models using GMM estimators.[30] The BS framework discussed above is most closely related to those models in that a linear dynamic process in TFP is assumed. In addition the GMM models suggest that TFP contains a fixed effect α_i so that

$$\omega_{it} = \alpha_i + v_{it} \tag{42}$$

where

$$v_{it} = \rho v_{it} + \nu_{it} \tag{43}$$

To estimate the resulting model we have to rely on dynamic panel data methods; i.e. we estimate a differenced version of an equation such as 41 with second lags of the revenue and production factor variables as instruments. Note that in order to handle fixed effects we must assume that the shock process evolves linearly. Another implication is that we need at least 3 periods of data to implement this approach. This might be a problem particularly in samples that are subject to random sampling.

Another, related framework was recently put forward by Katayama et al. (2003) (KLT). They suggest using the nested logit demand framework proposed by Berry (1994) to come up with plant level demand functions. This allows them to identify technical efficiency shocks and demand shocks separately which leads to the interesting and intuitive result that they are negatively correlated[31]. However, an important assumption in their strategy is that marginal costs are constant which not only requires a long run constant returns to scale production technology but also that capital adjusts instantly so that we are always in the long-run equilibrium. This might be restrictive in some applications.

3 The Data

I am using data from the Annual Respondents Database (ARD), the UK census of plants[32]. For plants of smaller firms, productivity data is collected on a random basis.[33]. I am using annual

[30]Compare the discussion in Griliches and Mairesse (1995).

[31]i.e. to produce better quality is more costly.

[32]More extensive descriptions of the ARD can be found in Barnes and Martin (2002), Criscuolo et al. (2003) Griffith (1999) and Oulton (1997)

[33]The threshold for random sampling has varied over the years. Firms with more than 250 employees are included fully in all years.

Table 1: Descriptive statistics

year	(1) obs	(2) mean employment	(3) mean $\frac{va}{l}$
1980	11712	346.35	19.14
1985	11109	296.32	23.04
1990	11085	279.03	26.53
1995	10734	228.65	33.44
1999	8958	188.15	33.85
2000	8632	182.60	33.88

Source: Author's calculations based on ARD data.
Notes: column 1 reports the number of observations with the full set of required variables.

data for the years 1980 to 2000. Because the econometric model outlined in section 2 requires current and lagged productivity data the sample reduces further. Table 1 reports sample sizes along with descriptive statistics for selected years. Because the ONS increased the plant size threshold for random sampling of plants the sample size is somewhat lower in later years[34]. The variables I am using are the standard revenue, employment head count, total labour costs and total intermediate purchases from the ARD. In the ARD survey plants are only asked to report their investments but not their capital stocks. I am therefore relying on a standard perpetual inventory method (PIM) to estimate plant level capital stocks.[35] Besides being dependant on assumptions about depreciation, this method requires a lot of interpolation: Firstly, we have to interpolate initial capital stock levels because some plants are born before our sample started and because plants might have already undertaken considerable amounts of investment by the time they are first surveyed. Secondly, we have to interpolate the investment levels of the randomly sampled smaller firms in the years when they are not sampled. A concern with this is that it introduces a source of measurement error into the capital stock variable that is typically ignored in most plant level productivity studies. I will leave a rigorous treatment of these issues for later research.[36] As a control for the severity of measurement of this kind I will use the following two variables: CENS measures the share of plants in a 3 digit sector that are born before the sample starts ; i.e. the share of plants that are subject to left censoring. INTERPOL measures the share of observations per sector that are interpolated because of random sampling.

4 Results

This section looks first at point estimates of $\frac{\gamma}{\mu}$, the coefficient on capital in equation 21. The estimation approach introduced in section 2 and the various alternative approaches discussed in section 2.4 differ primarily in the value they suggest for this parameter.

[34]What happened is that although the threshold was increased the actual sample size increased because more plants were sampled. But as a consequence of this the share of plants in the sample which is not observed consecutively in the sample has increased.

[35]For details see Martin (2002). Note that this is equivalent to the standard ARD capital stock series provided by the ONS.

[36]See Martin (2005) for a possible approach.

Table 2: Estimates of $\frac{\gamma}{\mu}$

	(1)	(2)	(3)	(4)	(5)
Sector	Mπ	OLS	LP	$NoExit$	MM
Food	0.87	0.97	0.90	0.87	0.87
Textile	0.87	0.96	0.85	0.86	0.87
Apparel	0.83	0.96	0.75	0.84	0.84
Leather	0.87	0.95	1.04	0.87	0.88
Wood	0.86	0.93	0.83	0.86	0.84
Paper	0.84	0.98	0.91	0.85	0.87
Publishing	0.88	0.95	0.92	0.89	0.97
Chemical	0.78	0.97	0.87	0.79	0.81
Plastic	0.76	0.96	0.98	0.77	0.81
Mineral	0.84	0.96	0.87	0.85	0.82
BasicMetalls	0.89	0.97	0.93	0.88	0.91
FabricatedMetalls	0.90	0.96	0.89	0.91	0.92
MachineryOther	0.85	0.97	0.92	0.86	0.85
OfficeMachinery	0.97	0.97	0.88	0.98	0.91
ElectricalMachineryOther	0.87	0.96	0.91	0.86	0.87
TVCommunication	0.88	0.95	0.85	0.88	0.87
OpticalPrecision	0.87	0.95	0.99	0.87	0.87
Vehicles	0.87	0.96	0.94	0.87	0.85
OtherTransport	0.85	0.97	0.99	0.85	0.88
Furniture	0.80	0.93	0.83	0.82	0.83
Average	0.86	0.96	0.90	0.86	0.87

Notes: Coefficients were estimated at the 3 digit level and then averaged up to 2 digit sectors. $M\pi$ refers to the capital coefficient obtained with the productivity estimator described in section 2, using net revenues to control for endogeneity and accounting for exit as well as measurement error in labour. OLS is a simple OLS estimator of equation 21. LPR is the original LP using their levpet.ado Stata programme in term of revenue. $NoExit$ is $M\pi$ without accounting for exit. MM is $M\pi$ but using material inputs to control for endogeneity.

Table 3: Estimates of productivity dispersion

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sector	$M\pi$	$\frac{VA}{L}$	TFP	Err	OLS	LPR	$NoExit$	MM
Food	0.63	1.40	0.38	0.68	0.46	0.82	0.62	0.49
Textile	0.50	0.91	0.34	0.60	0.48	0.61	0.51	0.44
Apparel	0.68	1.01	0.44	0.79	0.61	1.01	0.66	0.61
Leather	0.42	0.89	0.33	0.52	0.43	0.38	0.42	0.33
Wood	0.47	0.98	0.41	0.55	0.54	0.63	0.48	0.44
Paper	0.57	1.03	0.30	0.61	0.39	0.45	0.57	0.42
Publishing	1.34	1.33	0.63	1.39	0.79	0.97	1.38	1.67
Chemical	0.97	1.38	0.43	0.99	0.52	0.89	0.93	0.78
Plastic	0.84	0.98	0.37	0.91	0.53	0.44	0.84	0.59
Mineral	0.66	1.11	0.45	0.78	0.63	0.73	0.63	0.63
BasicMetalls	0.47	1.00	0.32	0.55	0.46	0.43	0.48	0.33
FabricatedMetalls	0.50	0.94	0.44	0.64	0.57	0.67	0.47	0.32
MachineryOther	0.62	0.94	0.37	0.73	0.52	0.61	0.59	0.53
OfficeMachinery	0.41	1.26	0.50	0.54	0.69	0.87	0.41	0.35
ElectricalMachineryOther	0.58	0.99	0.41	0.69	0.55	0.59	0.62	0.50
TVCommunication	0.59	1.23	0.49	0.67	0.60	0.94	0.59	0.57
OpticalPrecision	0.64	1.10	0.46	0.73	0.65	0.57	0.63	0.50
Vehicles	0.63	0.95	0.33	0.70	0.47	0.91	0.61	0.62
OtherTransport	0.75	0.98	0.46	0.87	0.68	0.59	0.75	0.52
Furniture	0.72	1.12	0.45	0.81	0.59	0.75	0.66	0.54
Average	0.64	1.08	0.41	0.72	0.54	0.69	0.63	0.54

Notes: The dispersion measure reported is the log difference between 90iest and 10th percentile. Dispersion measures were estimated at the 3 digit level and then averaged up to 2 digit sectors. $\frac{VA}{L}$ refers to labour productivity. TFP is standard factor share TFP as implicitly defined in equation 16. Err is TFVP based on the $M\pi$ approach but not correcting for measurement error in labour. For other column definitions see notes of table 2.

4.1 Estimates of $\frac{\gamma}{\mu}$

Table 2 reports estimates for estimates for $\frac{\gamma}{\mu}$ across sectors and different estimation methods. All figures are averages of estimates computed at the 3-digit level. For clarity they are reported at the 2-digit level.[37]

The last row reports averages for the economy as a whole. Column 1 uses my preferred method; i.e. employing net revenues to control for endogeneity, and accounting for exit and measurement error in labour inputs as described in section 2 (Mπ). Using standard factor share methods to compute TFP assumes that this coefficient is equal to 1. In column 1 we get an economy wide average of 0.86 suggesting that imperfect competition is an issue. Compared to a simple OLS regression of equation 21 reported in column 2 – i.e. ignoring any endogeneity issues – the coefficients are lower both for the economy wide as well as the 2 digit sectoral averages. This is in line with what one would expect: TFVP should be positively correlated with capital stocks. Not controlling for this endogeneity should then bias estimates upward. Column 3 reports results using the LP estimator which does not control for exit and uses material inputs as proxy for un-observed heterogeneity. This set of parameter estimates generally lies for the whole economy average in between the OLS estimates and my preferred specification. However in some sectors it actually leads to lower values than in column. I conclude therefore that the estimates are different rather than biased in a particular direction. Column 3 repeats the calculations of column 1 without accounting for exit. This leads to virtually the same results. Column 5 finally reports results from running my preferred specification using material inputs rather than net revenues as an argument in the control function for unobserved heterogeneity as suggested by LP. Again this leads to very similar estimates as column 1. Recall that the standard LP estimator as reported in column 3 differs from my estimator of column 1 in three respects:

1. Usage of materials rather than net revenues.
2. Not accounting for endogeneity through exit
3. Estimation of coefficient estimates on variable factors from a first stage regression rather than using the factor share based index in equation 11.

The last two columns of table 2 thus relax points 1 and 2 in my framework. As this does not affect estimates much differences between columns 1 and 3 must be driven by point 3. Two implications of point 3 are firstly, that the LP estimate uses a more restrictive production function with fixed factor shares and secondly it's estimates might be biased because of the identification issues pointed out in Ackerberg et al. (2007)

Table 4 reports correlations between the $\frac{\gamma}{\mu}$ coefficient estimates at the 3digit level. This leads to similar conclusions as we just derived from table 2; i.e. OLS estimates are the most different from my preferred specification (Mπ). LP type (LPR) estimates are more similar although the correlation is not strong. Not accounting for exit ($NoExit$) or using materials as control (MM) does lead to very similar estimates.

[37]Table 13 give a sense of the variation in $\frac{\gamma}{\mu}$ by reporting standard deviations across 3 digit sectors. Table 15 reports results for selected 3 digit sectors.

4.2 Estimates of productivity dispersion

Table 3 reports dispersion estimates for various productivity measures and TFP estimation methods. I measure dispersion by the log difference between the plant at the 90th and 10th percentile for 3digit sectors. The table reports averages of those for the 2-digit sectors and the economy as a whole.[38] Consider first the columns 1 to 3 which report the results based on the Mπ approach, labour productivity and standard factor share TFP. Overall and for the various 2-digit averages labour productivity dispersion is largest. Mπ dispersion ranges at 60 percent[39] of labour productivity dispersion on average. TFP leads to the smallest estimates averaging at 38 percent of labour productivity dispersion. This is what one would expect: the labour productivity measure does not account for plant level variations in the intensity of the different production factors. TFP on the other hand implicitly assumes that the coefficient on capital in equation 21 is equal to 1; i.e. too large. If capital is positively correlated with the composite of TFP and demand shock then this compresses the measured dispersion as too much of the variation in output is attributed to variation on capital stocks. Therefore, on average, $M\pi$ dispersion is 50 percent higher than TFP dispersion.

Column 4 reports dispersion estimates without correction for measurement error in labour as discussed in section 2.3. Dispersion not accounting for measurement error is on average 0.08 log points higher than the dispersion measure from column 1. This is much less than the deviation of 0.24 log points induced by measuring dispersion using standard TFP. Moreover it turns out that in some 3-digit sectors, not accounting for measurement error actually leads to lower dispersion.[40] The remaining columns of table 3 report dispersion estimates using different approaches to estimate equation 21 as already discussed in the previous sub section. We saw there that the estimates for the $\frac{\gamma}{\mu}$ parameter using a simple OLS estimate are rather high and very close to 1. Not surprisingly this leads to dispersion levels in column 5 that are close to the standard TFP levels in column 3. The LP estimator leads to comparatively very similar dispersion averages as the Mπ estimator. However, from table 5 which reports correlations of dispersion measures at the 3-digit sectoral level, we see that this is result is an artefact of aggregation. At the 3-digit level the LP based results are only related to Mπ results with a correlation coefficient of 0.629. Table 6 reporting correlations between the various productivity measures at the firm level reveals further that the correlation between LP and Mπ productivity is rather weak with a correlation coefficient of 0.52.

Table 4: Correlation between various estimates of $\frac{\gamma}{\mu}$ across 3 digit sectors

	(1) Mπ	(2) OLS	(3) LPR	(4) $NoExit$	(5) MM
$M\pi$	1.000	0.207	0.389	0.989	0.901
OLS	0.207	1.000	0.112	0.213	0.206
LPR	0.389	0.112	1.000	0.347	0.390
$NoExit$	0.989	0.213	0.347	1.000	0.907
MM	0.901	0.206	0.390	0.907	1.000

Notes: For definitions of the labels see the notes of table 2

[38] Table 14 provides standard deviations of the dispersion measures across 3digit sectors.

[39] 0.61 over 1.08

[40] See table 15 in the appendix.

Table 5: Correlation between various dispersion measures across 3 digit sectors

	(1) $M\pi$	(2) $\frac{VA}{L}$	(3) TFP	(4) Err	(5) OLS	(6) LPR	(7) $NoExit$	(8) MM
$M\pi$	1.000	0.476	0.664	0.989	0.571	0.629	0.985	0.838
$\frac{VA}{L}$	0.476	1.000	0.446	0.435	0.201	0.432	0.466	0.438
TFP	0.664	0.446	1.000	0.704	0.887	0.505	0.671	0.576
Err	0.989	0.435	0.704	1.000	0.640	0.623	0.972	0.825
OLS	0.571	0.201	0.887	0.640	1.000	0.373	0.571	0.453
LPR	0.629	0.432	0.505	0.623	0.373	1.000	0.588	0.596
$NoExit$	0.985	0.466	0.671	0.972	0.571	0.588	1.000	0.856
MM	0.838	0.438	0.576	0.825	0.453	0.596	0.856	1.000

Notes: for descriptions of the columns and rows see the notes for table 2.

Table 6: Correlation between various TFP measures

	(1) $M\pi$	(2) $\frac{VA}{L}$	(3) TFP	(4) Err	(5) OLS	(6) LPR	(7) $NoExit$	(8) MM
$M\pi$	1.00	0.53	0.35	0.88	0.47	0.52	1.00	0.82
$\frac{VA}{L}$	0.53	1.00	0.64	0.68	0.37	0.44	0.53	0.31
TFP	0.35	0.64	1.00	0.37	0.78	0.47	0.36	0.03
Err	0.88	0.68	0.37	1.00	0.20	0.47	0.88	0.71
OLS	0.47	0.37	0.78	0.20	1.00	0.46	0.47	0.17
LPR	0.52	0.44	0.47	0.47	0.46	1.00	0.51	0.41
$NoExit$	1.00	0.53	0.36	0.88	0.47	0.51	1.00	0.82
MM	0.82	0.31	0.03	0.71	0.17	0.41	0.82	1.00

Notes: for descriptions of the columns and rows see the notes for tables 2 and 3.

5 Why is productivity dispersed?

So far the paper has focused on the measurement of productivity and productivity dispersion. In this section I re-visit evidence that can help us to understand why there is productivity dispersion. Firstly, I look at transition matrices to examine the persistence of productivity over time. Then I look at the link between productivity dispersion and competition across sectors.

5.1 Dynamic characteristics of the productivity distribution

If productivity dispersion is driven by Schumpeterian factors such as selection, learning or vintage effects, then we expect that the position of a specific plant within the productivity distribution is not very persistent over time. We can examine this using transition matrices. Table 7 shows a three year transition matrix for the distribution of value added over employment; i.e. the cells of table 7 contain estimates of the probability that a plant that is in the bottom quintile in year t, say, moves to the second quintile in $t + 3$ (row 1 column 2). The last column of table 7 contains estimates of the probability that a plant exits between t and $t + 3$. What can table 7 tell us about the quality of the productivity dispersion? The striking feature concerning the plant level productivity distribution is its persistence.[41] The diagonal

[41] This is a result stressed by other authors before. Compare Baily et al. (1992), Bartelsman and Dhrymes (1998) or Haskel (2000).

Table 7: Transition matrix for $\frac{VA}{L}$

	20	40	60	80	100	exit
20	0.34	0.17	0.08	0.04	0.02	0.34
40	0.17	0.24	0.17	0.10	0.04	0.28
60	0.08	0.18	0.22	0.18	0.07	0.27
80	0.04	0.10	0.19	0.26	0.16	0.25
100	0.02	0.04	0.08	0.18	0.40	0.28
entry	0.22	0.19	0.18	0.19	0.21	0.00

Source: Author's calculations based on ARD data. Notes: The cells report estimates of transition probabilities; e.g. the cell in column 2 of row 1 reports what fraction of plants that were in the bottom quintile in a given year managed to move to the second quintile three years later. The exit column report what fraction exited over the three year interval. The entry row reports how entering plants are distributed across productivity quintiles. The switching of the 3 digit industry by a plant was treated as an exit with consecutive entry.

Table 8: Transition matrix for TFP

	20	40	60	80	100	exit
20	0.33	0.18	0.11	0.06	0.03	0.30
40	0.18	0.22	0.18	0.11	0.04	0.27
60	0.10	0.18	0.21	0.18	0.08	0.25
80	0.06	0.12	0.18	0.23	0.14	0.27
100	0.03	0.06	0.10	0.18	0.30	0.33
entry	0.22	0.18	0.17	0.19	0.24	0.00

Notes: see notes of table 7

Table 9: Transition matrix for TFVP

	20	40	60	80	100	exit
20	0.29	0.17	0.07	0.03	0.01	0.44
40	0.14	0.27	0.19	0.07	0.02	0.32
60	0.05	0.17	0.28	0.19	0.04	0.27
80	0.02	0.06	0.18	0.35	0.16	0.23
100	0.01	0.02	0.04	0.16	0.56	0.21
entry	0.29	0.20	0.18	0.17	0.16	0.00

Notes: see notes of table 7

Table 10: Regressions of productivity dispersion on markup ($\frac{\mu}{\gamma}$)

Productivity measure:	$M\pi$	LPR	OLS	$\frac{VA}{L}$
markup	1.765***			0.359**
	(0.185)			(0.175)
markupLevPet		1.538***		
		(0.135)		
markupOLS			1.019	
			(0.653)	
R-squared	0.533	0.643	0.030	0.050
N	82	74	82	81

Source: Authors calculations based on ARD.
Notes: Dependant variable is the productivity dispersion for various productivity measures. For a description of the dispersion measure and the dependant variable "markup" see notes of figure 1.

elements of the matrix in table 7 are much higher than the off diagonal elements, suggesting that plants are most likely to remain at their current position, rather than move up or down. Further, while the exit probability for bottom plants is highest the differences in exit probabilities are not very pronounced across quintiles. Thus the evidence seems to be at odds with a Schumpeterian view.

Table 8 shows the transition matrix for TFP.[42] It turns out that persistence does not change much, and the exit probability of top plants is now actually higher than for bottom plants, which is rather implausible. So what happens if we use TFVP, the productivity measure proposed in section 2 instead? Table 9 shows the probability that bottom plants stay in their position – i.e. persistence – is 5 percentage points lower and persistence of top plants 16 points higher compared to the labour productivity case. Exit probability of bottom plants is twice as high as that of top plants.

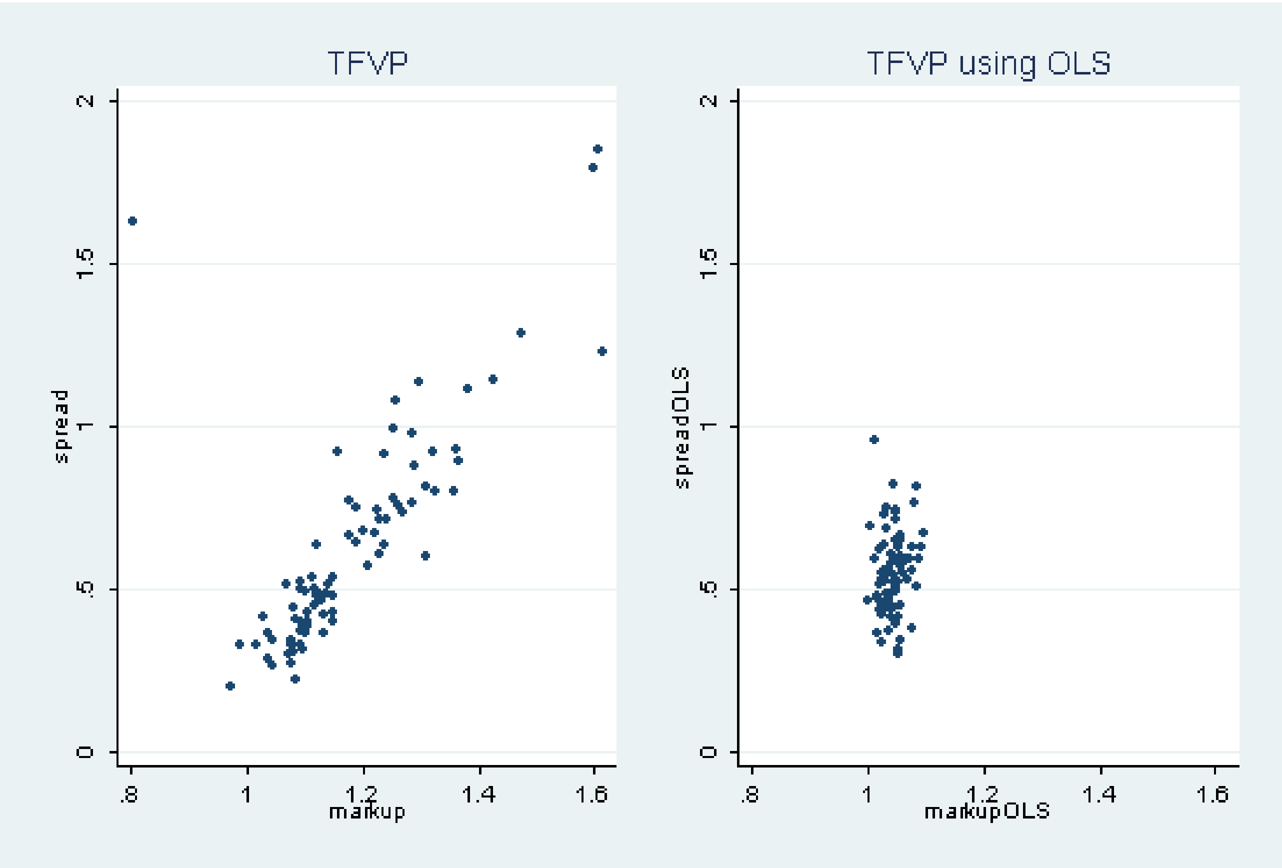
Overall, the transition matrix results suggest two things: Firstly, the TFVP productivity measure leads to more plausible dynamic features than standard TFP measures. Secondly, the persistence problem might be less serious than previously thought if plant level productivity is measured correctly.

5.2 Productivity dispersion and imperfect competition

Is there a link between competition and productivity dispersion? In my current framework the degree of (un)competitiveness is measured by μ the markup parameter. Unfortunately we can only estimate the ratio between the markup parameter μ and the scale parameter γ rather μ separately. However, if we are willing to assume that the variation of $\frac{\mu}{\gamma}$ across sectors is dominated by movements of μ then it might be worthwhile to look at the relation between $\frac{\mu}{\gamma}$ and productivity dispersion. Indeed, finding a positive correlation between markup and dispersion could be seen as a consistency of my framework. The left panel of figure 1 shows a scatter plot of TFVP dispersion and markups across 82 3digit sectors in my sample. With

[42] as defined in equation 16.

Figure 1: Productivity dispersion and markups across sectors



Source: Authors calculations based on ARD.
Notes: Dispersion is measured as the log difference between the productivity of the plant at the 90iest and the plant at the 10th percentile in 82 three digit manufacturing sectors. The percentiles are calculated on the pooled sample of median relative firm level productivity across the years. The median values are sector and time specific. Markup is the ratio between markup and scale parameter; i.e. $\frac{\mu}{\gamma}$. Thus, strictly speaking this corresponds to markup only under constant returns to scale. As discussed in section 2, with the current data it is not possible to identify the two parameters separately.
The left panel shows the result for the true spread (TVFP) estimator. The right panel shows the result applying an OLS estimator to equation 21.

Table 11: Measurement error and other factors affecting dispersion ($\frac{\mu}{\gamma}$)

Productivity measure:	$M\pi$	$M\pi$	$M\pi$	$M\pi$	$M\pi$	$\frac{VA}{L}$
markup	2.038***	1.608***	1.927***			
	(0.169)	(0.176)	(0.179)			
INTERPOL	-0.165***		-0.134**		-0.037	
	(0.054)		(0.057)		(0.089)	
CENS	-1.345***		-1.142***		0.160	
	(0.252)		(0.277)		(0.396)	
SUNK		-0.043	-0.019	-0.073*	-0.080**	-0.038*
		(0.026)	(0.025)	(0.038)	(0.039)	(0.020)
ADMIN		0.305	-0.032	0.601	0.602	0.407**
		(0.266)	(0.257)	(0.380)	(0.398)	(0.202)
TRANS		-1.125	-1.603	0.421	0.380	2.920**
		(1.672)	(1.531)	(2.394)	(2.418)	(1.273)
ADV		4.426***	3.445**	5.976***	5.790**	7.885***
		(1.499)	(1.406)	(2.143)	(2.209)	(1.139)
R-squared	0.660	0.623	0.694	0.209	0.215	0.493
N	82	82	82	82	82	82

Notes: See also the notes for table 10. INTERPOL is the share of observations in a 3digit sector where investment had to be interpolated (See section 3). CENS is the share of plants that were born before the start of the sample. SUNK is the measure of sunk costs in a sector as proposed by Sutton (1991) (see text for definition). ADMIN is the share of administrative workers. TRANS and ADV are the output share spend on road transport services and advertising, respectively.

the exception of an outlier[43] with high dispersion and low markup parameter, the relation appears very much as expected. Table 10 confirms this with a regression of markups of on productivity dispersion.[44] Column 1 corresponds to the relation in the figure. It implies that a 1 percent higher markup increases the distance between 90th and the 10th percentile plant by 1.7 percent. Column 2 repeats the exercise for dispersion estimates and markups derived from LP's framework. The coefficient is slightly smaller, but equally positive and significant. Column 3 suggests that these results might be sensitive to controlling for endogeneity in the regression step. Regressing dispersion on markups as derived from a simple OLS regression of equation 14 does not lead to a significant relationship between dispersion and markups. The right panel of figure 1 gives an illustration of this relation.

One concern with these results could be that they are spurious; i.e. as both, the dispersion and the markup measure depends on the underlying econometric framework, misspecification of the framework could generate both results even if there is no such relationship in reality. Measurement error in capital could be such a misspecification. Suppose that capital stocks in equation 14 are measured with error. This corresponds to a classical measurement error problem which would bias our estimate of the associated parameter - $\frac{\gamma}{\mu}$ in this case - downward. Then, if firms at the top end of the distribution have higher capital stocks, this would imply that the downward bias of the capital coefficient induces an upward bias in the dispersion measure. If the severity of this type of measurement error varies across sectors this could explain our results above. In table 11 I therefore repeat the regression of column 1 of table 10

[43]Sector 223, reproduction of recorded media

[44]Formally the regression model is $\omega_p 90 - \omega_p 10 = b\frac{\mu}{\gamma} + \epsilon$

introducing two variables that control for potential measurement error in capital. INTERPOL measures the share of observations in a sector that rely on interpolated investment figures whereas CENS measures the share of left censored observations.[45] The results in column 1 show that these variables are indeed strongly correlated with measured dispersion, however negatively. As a consequence it turns out that the relationship between estimated markup and dispersion becomes even stronger. Further evidence that the relationship is not driven by spurious reasons comes from the last column of table 10. It shows the result of a regression of dispersion in labour productivity[46] on estimated markups. While the relationship appears less strong it is still there.[47]

In a related study with US data Syverson (2004) refrains from computing substitution or markup parameters. Instead he links productivity dispersion to a number of other observed variables such as sunk costs, advertising intensity and transport costs. Some of these might affect dispersion by exerting an influence on product substitutability. Others might affect dispersion through other channels. The remaining columns of table 10 examine what happens if some of the factors that are important in Syverson's study are included in the analysis here. I am using a measure of the relevance of sunk costs (SUNK) defined as the market share of the median sized plant times the industry level capital-output ratio.[48] ADMIN is the average share of administrative employees in the industry. Syverson suggests that this is a measure of fixed costs. TRANS is the average output share of expenditure for road transport services. ADV is the average share of output spent on advertising. Column 3 of table 11 shows that only ADV is positive and significant when included as control in the dispersion regressions. Theoretically the relationship between advertising spending and dispersion could go either way. A positive relationship is consistent with the idea that more advertising leads to products being perceived by consumers as more differentiated. Also note that the coefficient on markup becomes somewhat lower which suggests that some of our controls affect dispersion by affecting markups. Column 4[49] examines this by repeating the regression without including markups. In addition to ADV, SUNK turns now out to be significant[50] as well however negatively. This is different from Syverson's result who found a positive relation. His theoretical motivation of this is that firms do not know about their specific productivity until they have paid the sunk cost. As a consequence there is less entry in markets with higher sunk costs but no stricter selection based on the quality of entrants. If firms have information on their productivity before paying the sunk cost there will still be less entry but at the same time their will be a stronger selection of entrants. Thus the relationship between sunk costs and dispersion can become negative. While this motivates my results the question remains for future research why we find diverge with UK vs US data.

Finally, column 6 repeats the regression of column 4 with labour productivity dispersion. This reveals that the positive relation with ADV and the negative relation with SUNK does not depend on my econometric model or measurement problems in capital. Interestingly, now the relation between transport cost shares and dispersion turns out to be significantly positive. This is in line with Syverson's findings although I use a different measure for transport costs.

[45]See also the discussion in the section 3

[46]i.e. value added over employment

[47]The result is only significant when dropping the outlier sector 223

[48]This is the same measure as Syverson uses who follows a suggestion by Sutton (1991).

[49]Column 3 repeats column 2 including controls for measurement error in capital. This leads to the same qualitative conclusions.

[50]At the 10 percent level that is.

Finally, ADMIN becomes positively significant. This is different from Syverson who finds in some of his specifications a negative relation. An explanation could be that the share of administrative employment is not so much a measure of the importance of fixed costs for an industry – as suggested by Syverson – but possibly more an indication of product differentiation and marketing efforts in addition to mere spending on advertising.[51] Still, the question remains why the results are different in the UK and US.

6 Conclusion

This paper proposes a novel framework for computing TFP by combining a refined version of the methodology of Olley and Pakes (1996) with the revenue production framework introduced by Klette and Griliches (1996). The framework allows for imperfect competition, a flexible production technology, non constant returns to scale, addresses the endogeneity of inputs problem in production function estimation and controls for measurement error in labour inputs. I provide Monte Carlo evidence showing that the suggested framework is more precise and robust to misspecification than competing approaches. Examining productivity dispersion across 3 digit sectors with this new framework I find that compared to standard TFP estimation methods measured dispersion increases on average by more than 50 percent. Further I find that the dynamic characteristics of the new TFP measure are more in line with a Schumpeterian view on productivity dispersion. Further work needs to consider more flexible specification for the demand structure. I outline in the Appendix how this could be done.

Examining the link between competition and dispersion across sectors I find that sectors with less competition – measured by less product substitutability – tend to have higher dispersion measured either in terms of the new TFP measure or labour productivity.

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[51]Supportive of this view is a positive and significant correlation between advertising and admin share.

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A The monotone relationship between net revenues and shocks

Start by noting that given our assumption of a homogenous production function 2 we can write the cost minimization problem as

$$\tilde{C}(\tilde{K}_{it}, \mathbf{w}_{Vit}) = \min_{\tilde{\mathbf{X}}_{Vit}} \sum_{z \neq K} w_{zit} \tilde{X}_{zit} \text{ s.t. } 1 = f\left(\tilde{K}_{it}, \tilde{\mathbf{X}}_{Vit}\right) \tag{44}$$

where $\tilde{K}_{it} = \frac{K_{it}}{\tilde{Q}_{it}}$ with $\tilde{Q}_{it} = \left(\frac{Q_{it}}{A_{it}}\right)^{\frac{1}{\gamma}}$. $\tilde{\mathbf{X}}_{Vit}$ collects the same transformation for all variable production factors in a vector. Total cost become in terms of equation 44

$$C_{it} = \tilde{C}_{it} \tilde{Q}_{it} \tag{45}$$

Next consider the profit function.

$$\Pi_{it}(K_{it}, \lambda_{it}, a_{it}, \mathbf{w}_{it}) = R_{it} - C_{it}$$

Given the demand function 6 and the cost function 45 we can write it as

$$\Pi_{it}(K_{it}, \lambda_{it}, a_{it}, \mathbf{w}_{it}) = \left(\frac{\Lambda_{it} R_t}{P_t}\right)^{\frac{1}{\eta}} P_t Q_{it}^{1-\frac{1}{\eta}} - \tilde{C}_{it} \tilde{Q}_{it} \tag{46}$$

Note that the firm's profit maximization first order condition is

$$\left(1 - \frac{1}{\eta}\right) \frac{R_{it}}{Q_{it}} = \frac{1}{\gamma} z(\tilde{Q}_{it}, \tilde{K}_{it}) \frac{\tilde{Y}_{it}}{Q_{it}} \tag{47}$$

where

$$z(\tilde{Q}_{it}, \tilde{K}_{it}) = \frac{\partial \tilde{C}_{it}}{\partial \tilde{Q}_{it}} \tilde{Q}_{it} + \tilde{C}_{it} \tag{48}$$

Finally, note that the derivatives of profit with respect to changes in λ_{it} and a_{it} are

$$\frac{\partial \Pi_{it}}{\partial \lambda_{it}} = \mu^{-1} R_{it}$$

and

$$\frac{\partial \Pi_{it}}{\partial a_{it}} = z(\tilde{Q}_{it}, \tilde{K}_{it}) \frac{1}{\gamma} \left(\frac{Q_{it}}{A_i t}\right)^{\frac{1}{\gamma}} = \mu^{-1} R_{it} \tag{49}$$

where the last equality follows from the first order condition 47[52] and

$$\mu = \left(1 - \frac{1}{\eta}\right)^{-1}$$

As a consequence of all these results we get for the total differential of profits

$$d\Pi_{it} = R_{it}\frac{1}{\mu}\left(d\lambda_{it} + da_{it}\right) = R_{it}d\omega_{it} \tag{50}$$

which establishes that there is a positive relationship between net revenues and the composite shock index ω_{it}.

B Existence of equilibrium with positive output

In section 2.4 I suggested that for the existence of a profit maximising equilibrium in which plants actually produce any output in a Dixit-Stiglitz setting we need that $\mu > \gamma$ in the long run equilibrium where capital stocks have fully adjusted; i.e. returns to scale must not be too high. This section shows this formally. With markup pricing equilibrium profits can be written as[53]

$$\Pi = \mu \cdot MC \cdot Q - C$$

where $C = Q^{\frac{1}{\gamma}}w$ are total costs, $MC = \frac{1}{\gamma}Q^{\frac{1}{\gamma}-1}w$ marginal costs and w is a composite index of the price of a cost minimising input bundle f[54], so that we get

$$\Pi = \left(\frac{\mu}{\gamma} - 1\right)Q^{\frac{1}{\gamma}}$$

Hence only for $\mu > \gamma$ profits would be positive. Consequently plants would not produce anything if this condition does not hold.

C Allowing for varying markups

This section outlines how the productivity estimation framework introduced in section 2 can be extended to account for more general demand specifications implying varying demand elasticities across plants. The basic idea is most easily grasped for a Cobb Douglas Production function. Note that for a variable production factor X, profit maximisation implies that

$$\frac{\alpha_X}{s_{xi}} = \mu_i \tag{51}$$

Thus, because α_X is constant in the Cobb-Douglas case, variations in revenue share s_{xi} are a proxy for variations in markup μ_i. With a more general production function the first order condition (Equation 7) implies that

$$\frac{\partial lnQ_i}{\partial lnX_i}\frac{1}{s_{xi}} = \mu_i \tag{52}$$

[52]This is an application of the envelope theorem

[53]To avoid notional clutter I drop plant and time indices in this section

[54]compare equation 2

Notice that with a Hicks neutral technology shock the log derivative of output with respect to a production factor is just a function of production factors; i.e.

$$\frac{\partial lnQ_i}{\partial lnX_i} = \Psi_Q\left(\mathbf{X_i}\right) \tag{53}$$

Importantly, all un-observed heterogeneity from variations in technical efficiency (a_it) vanishes. Thus markups are simply a function of observed production factors and the revenue share of a variable factor:

$$\mu_i = \Psi\left(\mathbf{X_i}, s_{xi}\right) = \frac{1}{s_{xi}}\Psi_Q\left(\mathbf{X_i}\right) = g_\mu\left(\mathbf{X_i}, s_{xi}\right) \tag{54}$$

We can use this to augment the control function approach developed in the main section. The equivalent of equation 21 would become

$$r_{it} - vi_{it} = g_\mu\left(\mathbf{X}_{it}, s_{xit}\right) k_{it} + g\left(\mathbf{X}_{it-1}, s_{xit-1}, \Pi_{it-1}\right) + \nu_{it} + \varsigma_{it} \tag{55}$$

To implement this equation we can approximate $g_\mu(\cdot)$ by a polynomial in $\mathbf{X}_{it}$ and s_{xit}. This adds the complication that the variable factors entering as arguments in $g_\mu(\cdot)$ are potentially correlated with the error term ν_{it}. Therefore to identify equation 55 we need to rely on a methods moments approach. The following conditions provide sufficient restrictions for identification:

$$E\left\{\left[\begin{array}{ccccc} X_{it-1}k_{it} & s_{xit-1}k_{it} & X_{it-1} & s_{xit-1} & \pi_{it-1}\end{array}\right]' \nu_{it}\right\} = 0 \tag{56}$$

To recover an index of firm level markups and thus the distribution of markups we can consequently compute

$$\frac{\mu_i}{\gamma} = \frac{k_{it}}{\widehat{g_\mu\left(\mathbf{X}_{it}, s_{xit}\right) k_{it}}} \tag{57}$$

D Monte Carlo Analysis

This section examines various production function estimation approaches which were discussed in section 2.4 using Monte Carlo Analysis. The model used to draw Monte Carlo samples uses a Cobb Douglas production function and a Dixit Stiglitz demand function with the following parametrisation: capital coefficient in the production function $\alpha_K = 0.15$, labour and intermediates coefficients $\alpha_L = \alpha_M = 0.425$, markup parameter $\mu = 2$, the standard error of the shock to TF(V)P $\sigma_\nu = 0.01$, standard error of the additional noise term $\sigma_\varsigma = 0.002$. I model persistence by assuming that input factors evolve as follows

$$x_{it} = (1 - \rho_x))\, x^*_{it} + \rho_x\left(x_{it-1} + \varepsilon_{xit}\right) \tag{58}$$

where x^*_{it} is the myopic optimal input demand conditional on capital and TFVP and ε_{xit} is an iid shock.[55] In the case of capital k^*_{it} is calculated as $k^*_{it} = k(E_{t-1}\{\omega_{it}\})$; i.e. the optimal capital stock in period t based on the expectation in $t-1$ about TFVP. I examine 3 different scenarios.

1. High persistence in both material inputs and labour with $\rho_M = 0.6$ and $\rho_l = 0.6$.

[55] This is somewhat ad hoc but suffices for the purpose here. Bond and Söderbom (2005) show how this could be extended using dynamic optimisation.

2. Little persistence in material inputs with $\rho_M = 0.06$ and $\rho_l = 0.6$.

3. Little persistence in both material and labour inputs with $\rho_M = 0.06$ and $\rho_l = 0.1$.

For each scenario I draw a sample with 200 firms over 10 time periods 100 times. Each time I estimate production function coefficients using 8 different models:

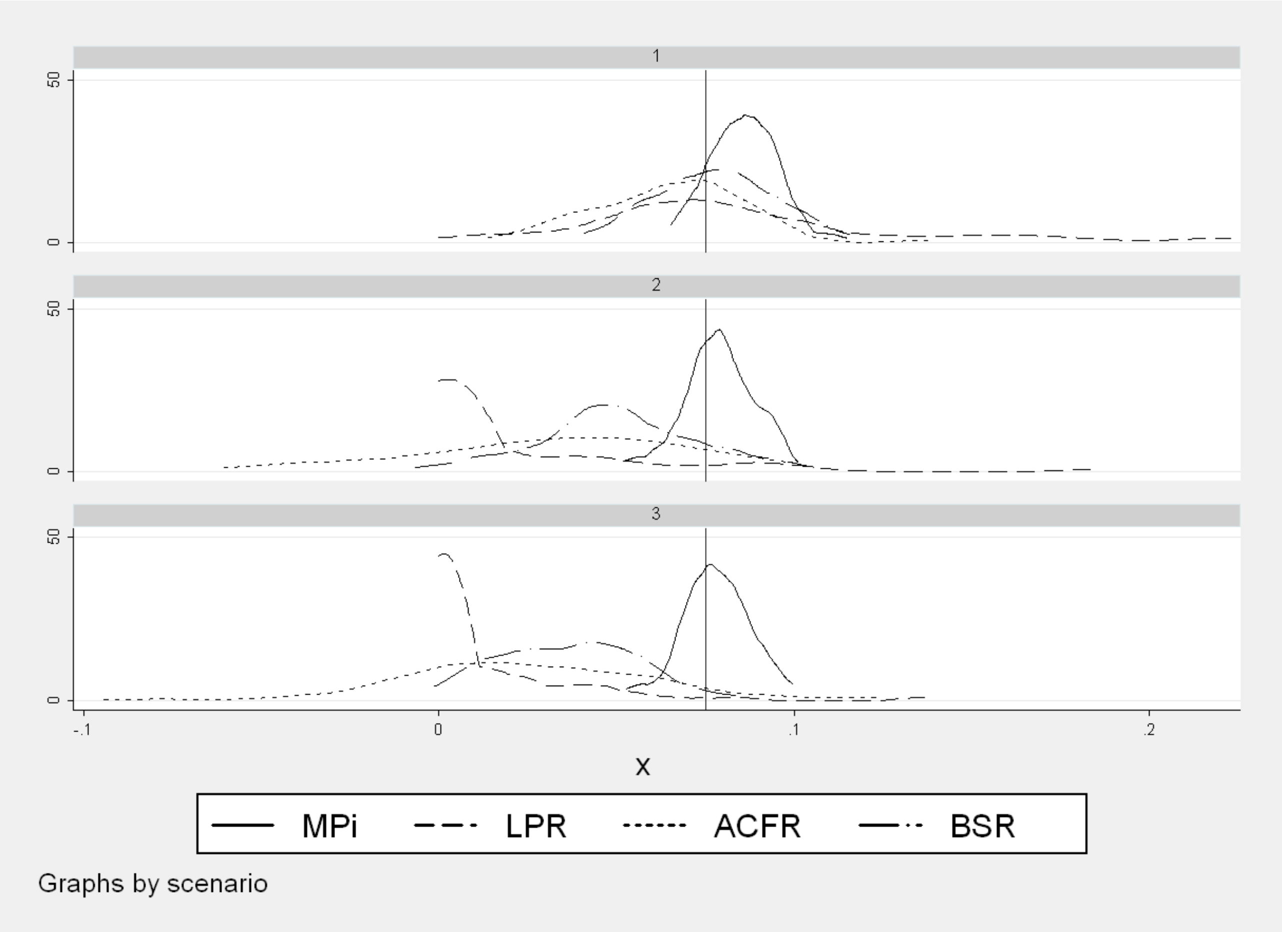
- Simple OLS (OLS)
- The M approach discussed above once using material inputs (MM) and once using net revenue as proxy (Mπ).
- The Levinsohn and Petrin approach with material inputs as proxy, once in a revenue production framework context (LPR) and once in terms of value added (LPVA)
- The framework proposed by Ackerberg, Caves and Frazer once in revenue (ACFR) and once in value added (ACFVA) terms.
- The approach suggested in Bond and Söderbom (2005) in terms of a revenue production function only (BS).

Table 12 reports statistics on the resulting estimates for the scale parameter which corresponds under imperfect competition to $\frac{\gamma}{\mu}$ - i.e. in the current context the true parameter value takes on a value of 0.5 - and the coefficient on capital which is equal to $\frac{\alpha_K}{\mu} = 0.075$. For each coefficient the table reports the mean point estimate over the 100 sample draws, the standard error of that mean as well as the 5th and 95th percentile of the 100 draws; i.e. the boundaries of a 90 percent confidence interval.

Consider first scenario 1. Persistence of all production factors is fairly strong. The estimator which does best under these conditions is BS with a bias of 0.078-0.075=0.003 for the capital coefficient and 0.037.[56] This is not surprising as for all estimators the persistence of materials introduces biases. In the case of the M and the LP estimators, however, persistence of labour introduces an additional reason for biases. Interestingly, the effect of this seems to be fairly strong for MM but not so strong for MΠ. Also note that the standard error of the M estimators are an order of magnitude lower than those of ACF or BS estimators and the biased MΠ is well within the 90 percent confidence interval around the BS estimate. Thus in finite samples this could imply that the probability of being wrong with the less biased estimate is much higher than with the more biased one. In Scenario 1 the persistence of material inputs is reduced to $\rho_M = 0.06$. Notice how this drives up the bias on the capital coefficient of the OLS estimate which now averages at -0.002 (column 5). This improves the performance of the M, the ACFVA and the LPVA. However, it creates massive problems for revenue (rather than value added version of ACF and LPV (ACFR,LPVR) because it becomes increasingly difficult to identify all the parameters. Notice that these estimators become increasingly biased towards the OLS estimator which reflects that the lagged values of the factor input variables become weaker as instruments. The last scenario finally, also reduces the persistence in labour inputs. This give the M estimates an additional boost as their biases are now greatly reduced. At the same time, the estimates that rely on value added production function start to deteriorate as they are not identified. In summary, the M estimators perform well if the underlying assumptions are approximately met. The biases introduced by persistence in labour and or materials

[56] The only bias for BS comes from the ς shock term.

Figure 2: Density plots of the coefficient estimates for $\frac{\alpha_K}{\mu}$



Source: Authors calculations based on Monte Carlo data.
Notes: Each panel refers to a different Monte Carlo scenario as discussed in the text and in table 12.

seem small compared to the errors that are introduced by the lower precision of alternative estimators. Figure summarises this graphically by reporting density plots of estimates using different methods for the 3 scenarios considered.

Table 12: Results from a Monte Carlo Analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\frac{\gamma}{\mu}$				$\frac{\alpha_{\mathbf{K}}}{\mu}$			
Model	**mean**	**error**	**p5**	**p95**	**mean**	**error**	**p5**	**p95**
Scenario 1: High persistence in M and L; ρ_M=0.6 ρ_l=0.6								
OLS	0.728	0.002	0.705	0.759	0.071	0.001	0.055	0.087
MM	0.529	0.001	0.511	0.549	0.104	0.001	0.086	0.124
M Π	0.511	0.001	0.496	0.524	0.086	0.001	0.071	0.099
LP R	0.810	0.029	0.427	1.294	0.084	0.005	0.021	0.179
LP VA	0.632	0.001	0.608	0.656	0.093	0.001	0.078	0.109
ACF	0.756	0.014	0.473	0.987	0.065	0.002	0.029	0.097
ACF VA	0.698	0.011	0.518	0.883	0.067	0.002	0.032	0.106
BS	0.537	0.006	0.431	0.624	0.078	0.002	0.049	0.106
Scenario 2: Low persistence in M; ρ_M=0.06 ρ_L=0.6								
OLS	1.006	0.000	0.998	1.013	-0.002	0.000	-0.006	0.002
MM	0.501	0.001	0.483	0.518	0.076	0.001	0.058	0.093
M Π	0.504	0.001	0.486	0.520	0.079	0.001	0.061	0.095
LP R	1.001	0.025	0.435	1.214	0.018	0.004	0.000	0.088
LP VA	0.500	0.001	0.483	0.517	0.078	0.001	0.062	0.092
ACF	0.770	0.024	0.414	1.170	0.033	0.004	-0.041	0.093
ACF VA	0.537	0.009	0.359	0.655	0.068	0.001	0.046	0.092
BS	0.716	0.014	0.496	0.940	0.050	0.002	0.012	0.092
Scenario 3: Low persistence in M and L; ρ_M=0.06 ρ_L=0.1								
OLS	1.010	0.001	1.001	1.019	-0.003	0.000	-0.008	0.002
MM	0.501	0.001	0.481	0.517	0.076	0.001	0.056	0.092
M Π	0.503	0.001	0.484	0.520	0.078	0.001	0.059	0.095
LP R	1.069	0.024	0.635	1.362	0.012	0.002	0.000	0.051
LP VA	0.621	0.002	0.592	0.651	0.058	0.001	0.043	0.072
ACF	0.795	0.023	0.450	1.120	0.026	0.004	-0.029	0.081
ACF VA	0.698	0.023	0.390	1.220	0.037	0.003	-0.044	0.079
BS	0.747	0.012	0.552	0.961	0.036	0.002	0.004	0.068

Notes: The table reports descriptive statistics from parameter estimates of 100 replications of a sample with 200 firms over 10 years. There are three scenarios and 8 models. MM and M π are the M approach using materials and net revenue as proxy in the control function, LPR and LPVA are the LP framework in a revenue and value added production function context, ACF refers to the ACF framework and BS to the BS framework. The sample was created using a Cobb Douglas production function and a Dixit Stiglitz demand structure. For more details on the underlying model see the text. The true parameter values for the scale parameter and the capital coefficient are 0.5 and 0.075.

E Additional Results

Table 13: Standard deviation of $\frac{\gamma}{\mu}$ estimates across 3digit sectors

	(1)	(2)	(3)	(4)	(5)
Sector	Mπ	OLS	LP	$NoExit$	MM
Food	0.11	0.02	0.21	0.11	0.08
Textile	0.10	0.01	0.11	0.10	0.10
Apparel	.	.	.	.	.
Leather	0.05	0.02	0.05	0.06	0.05
Wood	0.07	0.01	0.05	0.07	0.05
Paper	0.04	0.00	0.03	0.03	0.04
Publishing	0.31	0.02	0.09	0.33	0.44
Chemical	0.10	0.01	0.16	0.08	0.08
Plastic	0.04	0.01	0.08	0.05	0.09
Mineral	0.13	0.03	0.17	0.12	0.14
BasicMetalls	0.02	0.01	0.08	0.02	0.03
FabricatedMetalls	0.09	0.02	0.11	0.09	0.09
MachineryOther	0.09	0.01	0.11	0.09	0.08
OfficeMachinery	.	.	.	.	.
ElectricalMachineryOther	0.08	0.01	0.11	0.10	0.08
TVCommunication	0.08	0.02	0.13	0.07	0.11
OpticalPrecision	0.06	0.01	0.10	0.06	0.06
Vehicles	0.04	0.02	0.17	0.04	0.03
OtherTransport	0.08	0.01	0.05	0.08	0.10
Furniture	0.07	0.02	0.17	0.06	0.08
Average	0.10	0.02	0.13	0.10	0.11

Notes: For column definitions see table 2. The table reports the standard deviation of estimates of $\frac{\gamma}{\mu}$ across the 3digit sectors within a 2digit category with sufficient observations to conduct a separate analysis. Note that Apparel and OfficeMachinery consist only of one such 3digit sector and therefore no standard deviation can be computed.

Table 14: Standard deviation of dispersion measures across 3digit sectors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sector	$M\pi$	$\frac{VA}{L}$	TFP	Err	OLS	LPR	$NoExit$	MM
Food	0.54	0.29	0.22	0.52	0.21	0.68	0.54	0.38
Textile	0.24	0.12	0.04	0.22	0.04	0.25	0.26	0.21
Apparel	.	.	.	.	.	.	.	.
Leather	0.19	0.16	0.12	0.21	0.10	0.09	0.20	0.16
Wood	0.09	0.07	0.09	0.09	0.11	0.06	0.11	0.09
Paper	0.14	0.13	0.00	0.09	0.04	0.02	0.11	0.14
Publishing	0.26	0.33	0.10	0.21	0.05	0.37	0.35	1.09
Chemical	0.53	0.20	0.11	0.53	0.13	0.61	0.42	0.40
Plastic	0.12	0.15	0.02	0.14	0.07	0.06	0.13	0.28
Mineral	0.34	0.09	0.07	0.26	0.06	0.41	0.31	0.37
BasicMetalls	0.09	0.16	0.03	0.08	0.04	0.16	0.10	0.15
FabricatedMetalls	0.23	0.07	0.07	0.19	0.10	0.21	0.19	0.19
MachineryOther	0.29	0.08	0.06	0.24	0.06	0.21	0.29	0.32
OfficeMachinery	.	.	.	.	.	.	.	.
ElectricalMachineryOther	0.32	0.13	0.05	0.28	0.08	0.14	0.42	0.29
TVCommunication	0.21	0.14	0.05	0.24	0.06	0.37	0.22	0.36
OpticalPrecision	0.24	0.08	0.05	0.19	0.07	0.04	0.24	0.17
Vehicles	0.27	0.17	0.03	0.24	0.02	0.68	0.19	0.32
OtherTransport	0.23	0.14	0.06	0.18	0.11	0.06	0.22	0.31
Furniture	0.23	0.15	0.04	0.19	0.05	0.41	0.20	0.24
Total	0.34	0.22	0.11	0.31	0.12	0.36	0.33	0.39

Notes: For column definitions see table 3. The table reports the standard deviation of estimates of the productivity spread across 3digit sectors within a 2digit category with sufficient observations to conduct a separate analysis. Note that Apparel and OfficeMachinery consist only of one such 3digit sector and therefore no standard deviation can be computed.

Table 15: The 5 sectors where the dispersion is highest and lowest

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sectors with highest true spread							
Sector	**obs.**	$\frac{\gamma}{\mu}$	$\mathbf{log}\left(\frac{\mathbf{VA}}{\mathbf{L}}\right)$	$(\omega+\varrho)$	ω	**%Meas.Error**	**%True spread**
Pharmaceuticals (244)	1231	0.622	1.534	1.879	1.851	0.018	1.207
Beverages (159)	2399	0.625	1.815	1.777	1.794	-0.009	0.988
Reproduction of Recorded Media (223)	85	1.244	1.706	1.620	1.627	-0.004	0.954
Printing (222)	3862	0.678	1.090	1.349	1.282	0.061	1.177
Bricks, Tiles (264)	508	0.619	1.083	1.224	1.226	-0.002	1.132
Sectors with lowest true spread							
Sector	**obs.**	$\frac{\gamma}{\mu}$	$\mathbf{log}\left(\frac{\mathbf{VA}}{\mathbf{L}}\right)$	$(\omega+\varrho)$	ω	**%Meas.Error**	**%True spread**
Knitted and Crocheted Fabrics (176)	114	1.030	0.740	0.290	0.199	0.123	0.270
Tanning of leather (191)	224	0.921	0.859	0.293	0.219	0.087	0.255
Batteries (314)	193	0.960	0.895	0.387	0.264	0.137	0.295
Fish processing (152)	438	0.929	1.229	0.357	0.273	0.068	0.222
Weapons and Amunition (296)	264	0.964	0.859	0.521	0.285	0.275	0.331

Notes: Column 2 reports the number of observations in the sample, column 3 the capital coefficient using the TFVP procedure outlined in section 2, column 3 to 6 report productivity spread (ln(90th)-ln(10th) percentile) for labour productivity, TFVP without accounting for measurement error in labour inputs and TFVP. Column 7 is (5-6)/4. Column 8 is 6/4.

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The Centre for Economic Performance Publications Unit
Tel 020 7955 7673 Fax 020 7955 7595 Email info@cep.lse.ac.uk
Web site http://cep.lse.ac.uk