TFP Estimation at Firm Level:

The Fiscal Aspect of Productivity Convergence in the UK

1. Introduction

Productivity growth in the UK has been sluggish during the last ten years following a similar trend in many OECD countries (McMorrow et al., 2010; Braconier et al., 2014). The consensus in the literature has been how policy changes affect productivity performance, including product and labour market regulations (Bourlès et al., 2013; Andrews and Cingano, 2014; Bravo-Biosca et al., 2016). There is very limited evidence on how fiscal changes affect productivity at the firm level (Arnold et al., 2011), which is a vital issue given the evolution of recent literature about firm heterogeneity and public policy changes (Bernard et al., 2012). The present paper aims to understand the evolution of firm Total Factor Productivity (TFP)[1] in a large group of UK Manufacturing Firms during a period of substantial financial turbulence and changes in the corporate tax schedule.[2]

A central issue in implementing this empirical investigation is to obtain reliable measures of TFP at the firm level. We treat this part of the analysis systematically and not as a trivial mechanical process. There is a bulk of literature focusing on alternative approaches for the estimation of productivity (Biesebroeck, 2007; Eberhardt and Helmers, 2010; Del Gatto et al., 2011; Van Beveren, 2012). Nonetheless, the enormous heterogeneity across firms suggests that the appropriateness of each method for TFP calculation depends on the nature of data in use and more importantly to what extent the underlying assumptions of each method are compatible to the data generating process (DGP). Conceptually, TFP is a residual which represents the amount of output that cannot be explained by the use of inputs. This definition highlights the existence of unobservables in the productivity measurement that should be controlled accurately in order to avoid misspecification and errors in TFP computations. The contribution of the paper is twofold: first, we provide a comprehensive discussion of the most up to date approaches in measuring TFP including non-parametric, parametric and semi-parametric techniques that we apply in a large data set of UK manufacturing firms over the period 2004-2011. The objective of this illustration seeks to compare merits and weaknesses of each methodology and then to identify the degree of

[1] The terms TFP and productivity are used interchangeably throughout the paper.

[2] There was a change in statutory corporate tax rate from 0% to 19% in 2006 for small firms, while the tax rate was reduced for medium sized enterprises from 23.75% to 19%. Other variations also apply for large sized enterprises during 2004-2011 (see Appendix 2).

correlation and commonality across TFP methods. This part of the analysis is also used to evaluate the effect of the 2009 global financial crisis on the TFP evolution of UK Manufacturing firms. The second part of the paper, which is our second contribution, investigates the effects of tax burden on TFP assessing whether the nature of the corporate tax-TFP relationship is robust or subject to TFP computation choices and definition of variables.

Regarding the nexus of corporate tax-TFP, the paper puts forward a simple as well as an intuitive hypothesis that a higher level of profit tax bill induces distortive effects on productivity growth. This argument draws upon the fiscal effects on R&D on the one hand (Hall and Van Reenen, 2000) and on investment and entrepreneurship (Djankov et al., 2010) on the other. Both strands of the literature highlight the existence of two mechanisms though which corporate taxation can generate distortive effects on firm performance (Lucas, 1990)[3]. First, a higher statutory tax increases the user cost of capital, which might serve as a disincentive for gaining higher profitability through the use of new capital equipment (Fullerton, 1987; Hubbard, 1998; Devereux and Griffith, 2003).[4] Second, more recent studies (Keuschnigg and Ribi, 2013; Brekke et al., 2014) associate corporate tax liabilities with the existence of moral hazard and asymmetric information between the firm and its external creditors. As firms operate under financial constraints, their current income is the main asset that can be promised for loan repayment, and, therefore, anything that decreases cash flows and working capital such as tax liability can also weaken the borrowing capacity of the firm. Following this argument, the weakening of borrowing capacity due to lower post-tax income undermines the ability to invest in productivity enhancing investment; thus productivity growth slows down.

The effect of a weaker borrowing capacity due to higher tax liability affects disproportionally the groups of firms that are typically more risk-takers, and thus more dependent on the use of external finance (Cullen and Gordon, 2007; Bricongne, 2012). Representative examples of firms with greater exposure to risk are R&D and exporting firms. R&D activity usually encounters substantial sunk costs that must be covered up-front and will require substantial liquidity usually obtained from external creditors. In addition, R&D projects always involve a high degree of uncertainty, which generates pressure for cash-flows

[3] Lucas (1990) supports the view that corporate income should not be taxed in the long run as this income is the main engine of investment and growth (also see Zellner and Ngoie, 2015).
[4] The effect of corporate income tax on investment is initially founded in the seminal paper of Modigliani and Miller (1958). In their set up, firms operate in a financially unconstrained environment; so a higher level of marginal corporate tax affects only the marginal cost of investment. In a more complex business environment corporate tax might also impact a firm's ability to gain external finance.

and sufficient working capital, covered from external financial sources (Mánez et al., 2014). Firms prefer outsourcing research activities in geographical regions with low corporate tax while locating final production units in markets with high consumer tax rates (i.e., VAT) (Dischingier and Riedel, 2011). This within-firm fragmentation of production implies that R&D firms make decisions regarding location of research activities taking into account the corporate tax regime.

In a similar line of argument, exporters encounter higher levels of business costs relative to non-exporters due to the establishment of new market and transportation networks, which require substantial financial strength (Görg and Spaliara, 2014). Reducing the scale of research and export activity due to higher corporate tax liabilities is likely to induce substantial productivity losses that might affect both the evolution of TFP and the catch up process towards the frontier.

The paper is organized as follows: section 2 overviews five main approaches in the measurement of TFP at the firm level; section 3 shows results from a neo-Schumpeterian model of TFP catch up which permits us to assess the role of corporate tax on both the rate of TFP growth and TFP convergence, and section 4 concludes the paper.

2. TFP Estimation: Methodology and Measurement

2.1 Non-Parametric Techniques and Superlative Index Numbers

We start with the index number approach in the TFP measurement. The main advantage of this approach is the degree of flexibility in accommodating different underlying production functions. Additionally, this non-parametric approach avoids the usual econometric bias in the estimation of production input parameters. Nonetheless, the index number approach uses some fairly strong economic assumptions with the most prominent being the existence of perfect competition in product and input markets. Let us specify a standard Cobb-Douglass production function:

$$Y_{it} = A_{it} K_{it}^{a_k} L_{it}^{a_l} \qquad [0.1]$$

K and L represent capital stock and labour input for firm *i* at year *t*, parameter *A* stands for Hicks neutral technical change (TFP). Based on this set-up, productivity is derived as:

$$A_{it} = \frac{Y_{it}}{K_{it}^{1-a} L_{it}^{a}} \qquad [0.2]$$

Equation [2.2] expresses productivity (the ratio of output to weighted capital and labour). The weight is the share of labour a calculated as labour cost to value added, and under the assumption of constant returns to scale, capital share is $1-a$. Because the aggregate sum of inputs is not scale invariant, the TFP measures make better sense if they are compared to a reference point. In the seminal work of Solow (1957), production units are characterized from cost minimizing behavior; so the TFP formula can be viewed as a discrete approximation to the Divisia index. Caves et al. (1982) provide a broader interpretation of this, considering that the Tőrnqvist index number has a broader validity as it allows the derivation of TFP from more flexible underlying production functions such as the translog. The Tőrnqvist index proposed in Caves et al., (1982) is:

$$TFP \equiv (\ln Y_{it} - \ln \overline{Y}_t) - [\tilde{a}_{it}^L (\ln L_{it} - \ln \overline{L}_t) + (1-\tilde{a}_{it}^L)(\ln K_{it} - \ln \overline{K}_t)] \qquad [0.3]$$

With $\tilde{a}_{it}^L = \dfrac{a_{it}^L + \overline{a}_t^L}{2}$, upper bar in labour share represents the arithmetic mean across all observations in the sample in year *t*, while upper bars above inputs and output denote geometric means in year *t*. There are two disadvantages with the Tőrnqvist index specified in [2.3]; first labour share a is in fact a revenue share and it is biased if market structure deviates from perfect competition, which raises the need to adjust observed labour shares to total cost.[5] Second, this approach does not allow for any measurement error, which is easily accommodated in parametric estimations.

2.2 Parametric Estimates of TFP and Simultaneity Bias

The next family of estimators specifies a parametric log-linear form (letters in lower cases) of the production function [2.1] in order to recover estimates for labour and capital shares.

$$y_{it} = a_0 + a_k k_{it} + a_l l_{it} + \omega_{it} + \varepsilon_{it} \qquad [0.4]$$

The technical efficiency parameter is decomposed as follows: $\ln A_{jt} = a_0 + \omega_{it} + \varepsilon_{it}$, ω_{it} and ε_{it} are i.i.d idiosyncratic error terms. It is assumed that ω_{it} is an unobserved factor that affects firm *i*'s output, ε is a random noise to capture measurement error, and constant a_0 represents mean efficiency across all firms. In parametric estimations, parameter ω_{it} is further

[5] See Hall (1998), Roeger (1995) and De-Loecker (2012) for the construction of price mark-ups associated with the measurement of market power.

decomposed to include firm (η_i) specific and time (λ_t) specific effects. Therefore, an estimating specification of [2.4] takes the form:

$$y_{it} = a_0 + a_k k_{it} + a_l l_{it} + \eta_t + \lambda_t + \omega_{it} + \varepsilon_{it} \qquad [0.5]$$

In estimating parameters a_k and a_l with OLS raises the issue of selection bias between unobserved productivity shocks $\omega_{i,t}$ - which is observed for the firm but remain unobserved for the econometrician - and inputs *k* and *l* in period *t*.[6] In the presence of selection bias, the exogeneity assumption $\mathrm{E}[\omega_{it} l_{it}] \neq 0$ is violated leading to an upward bias of labour coefficient ($\hat{a}_k > a_k$).

A approach potentially suitable for tackling selection bias includes the instrumentation of *k* and *l* using either dynamic panel estimators or control function approaches. In dynamic panel estimations, endogeneity bias can be addressed by using input prices as instruments. In theory, prices can serve as valid instruments as being informative about input quantities while being unaffected from firm choice. The empirical implementation of this strategy is rather challenging as firm specific prices at micro level are rare while the use of industry specific price has limited variation causing instrument identification problems (Katayama et al., 2009). A commonly used approach is own instrumentation of endogenous variables within Generalized Methods of Moments (GMM) framework. The main motivation for a GMM estimation of [2.5] is associated with the high degree of persistence in ω_{it} that is assumed to follow an AR(1) process:

$$\omega_{it} = \rho\omega_{it-1} + \theta_{it} \text{ with } |\rho| < 1 \text{ and } \theta_{it} \sim MA(0) \qquad [0.6]$$

To address persistence, equation [2.5] is transformed into an Autoregressive Distributed Lag (ARDL) model with the inclusion of lag *y* as well as lags of *k* and *l* on the right-hand side:

$$\begin{aligned} y_{it} &= \rho y_{it-1} + \alpha_k k_{it} - \rho\alpha_k k_{it-1} + \alpha_l l_{it} - \rho\alpha_k l_{it-1} \\ &\quad + (1-\rho)(a_0 + \eta_i) + (\lambda_t + \rho\lambda_{t-1}) + \theta_{it} + (\varepsilon_{it} - \rho\varepsilon_{it-1}) \end{aligned} \qquad [0.7]$$

The unobserved productivity term ω_{it} is now removed in this representation, nonetheless there is still bias between lagged y_{it} and θ_{it}, which casts serious doubts about the appropriateness of standard OLS and FE estimators.[7] Estimation of [2.7] calls for the use of

[6] This is also known as transmission bias from unobservable productivity realisations to input choices (Eberhardt and Helmers, 2010).

[7] The bias of estimating a dynamic model with the lagged dependent variable on the right hand side is of the order 1/T, where T is the number of time series (Nickell, 1981). Monte Carlo experiments show (Judson and Owen, 1999) that FE and OLS cannot address this bias satisfactorily in panels with large cross-sections and short time series, as it is the dimensionality of the present data set.

valid instruments that need to satisfy two conditions: (a) being correlated with the endogenous regressors, and (b) being uncorrelated with the error term θ_{it} (which is now part of the productivity component). The lags of *k* and *l* are possible set of instruments for y_{it-1}, Δk_{it-1} and Δl_{it-1} (Wooldridge, 2009). A potential issue with this instrumentation strategy is the high degree of persistence in the DGP of inputs, which points to weak identification (as it is also the case with industry specific input prices as instruments). To overcome weak identification problems, the system GMM (GMM-SYS, hereafter) Blundell and Bond (1998) is developed, which uses the same principles of the differenced specification of [2.7] adding two moment restrictions that inputs in lagged differences are uncorrelated with the error term θ_{it}, $\mathrm{E}[\Delta k_{it-s}\theta_{it}]=0$ and $\mathrm{E}[\Delta l_{it-s}\theta_{it}]=0$. This assumption allows estimating directly the untransformed production function [2.5] using as instruments the second order lags of inputs in differences. The validity of these moment conditions depends on the absence of serial correlation in ε_{it}. The GMM-SYS estimator is regarded as the best option among the parametric approaches for addressing simultaneity bias and random measurement errors in both output and inputs (Griliches and Mairesee, 1995; Van Biesebroeck, 2007).[8] Bond and Söderbom (2005) provide a structural motivation for the appropriateness of GMM-SYS estimator, which assumes that all inputs are subject to variant adjustment costs. Therefore, the optimal choice of inputs across firms varies, providing a more theoretical justification for the use of lagged inputs as identifying instruments for the values of current inputs.[9]

2.3 Semi Parametric Estimates

2.3.1 Olley and Pakes Algorithm

The first semi-parametric approach in estimating a production function is initiated from Olley and Pakes (1996) (OP hereafter). The initial set-up is a Cobb-Douglass similar to [2.1] using a more structural framework for deriving production input estimates. They first set up a profit maximisation problem to derive investment as a proxy for the unobserved productivity ω_{it}.[10] Every period *t* firm *i* decides whether to "exit" or "stay" in the market. In the conditional "stay" decision *i* also decides the amount of investment *I* and labour *l*. Capital

[8] An additional advantage of system GMM is that Blundell and Bond (1998) estimators provide over identification test for the validity of instruments.
[9] There is dynamic dependence in inputs; so lagged values provide information about the amount of adjustment costs.
[10] This section shows the estimation procedure for more technical aspects of this algorithm; we refer the reader to Ericson and Pakes (1995) and Olley and Pakes (1996).

stock is accumulated as: $k_{i,t} = (1-\delta)k_{i,t} + i_{i,t-1}$. The investment function depends on two state variables, capital stock k_{it} and productivity ω_{it}, $i_{it} = i(\omega_{it}, k_{it})$. Given that the investment is strictly monotonic, we can define the inverse investment function:

$$\omega_{it} = h(k_{it}, i_{it}) \text{ with } h = i^{-1}(.) \qquad [0.8]$$

By substituting equation (2.8) into (2.4), the production function becomes as follows:

$$y_{it} = a_l l_{it} + \phi(k_{it}, i_{it}) + \varepsilon_{i,t} \qquad [0.9]$$

where $\phi(k_{it}, i_{it}) = a_0 + a_k k_{it} + h(k_{it}, i_{it})$. The OP algorithm is implemented in two stages, in the first stage, an OLS is used to estimate [2.9] to get values for the labour coefficient a_l (the variable input). Function $\phi(k_{it}, i_{it})$ is approximated by an higher order polynomial in i_{it} and k_{it}.[11] In the second stage, the OP algorithm runs a regression of $y_{it} - \hat{a}_l l_{it}$ on $\hat{\phi}_{it}(k_{it}, i_{it})$ in order to obtain an estimate for a_k (the state input). To recover the capital coefficient, it is assumed that productivity ω_{it} follows a first order Markov process: $\omega_{it} = \mathrm{E}\left[\omega_{it} \mid \omega_{it-1}\right] + \theta_{it}$, where θ_{it} is a an idiosyncratic error term of the productivity function. Plugging into the Markov process of the inverse investment function, we get:

$$\omega_{it} = \mathrm{E}\left[\omega_{it} \mid \omega_{it-1}\right] + \theta_{i,t} = f(\omega_{it-1}) + \theta_{it} = f(\phi_{it-1}(i_{it-1}, k_{it-1}) - a_0 - a_k k_{it-1})) + \theta_{it} \quad [0.10]$$

Intuitively, equation [2.10] states that unobserved productivity at time *t* is a function of observed productivity at *t*-1. Substituting [2.10] into the production function, we derive the estimating equation of the second stage in the OP algorithm.

$$y_{it} - \hat{a}_l l_{it} = a_k k_{it} + f(\hat{\phi}_{it-1}(i_{it-1}, k_{it-1}) - a_0 - a_k k_{it-1})) + \theta_{it} + \varepsilon_{it} \qquad [0.11]$$

Function *f*(.) is a control function approximated by a higher order polynomial and its estimated coefficient has no economic interpretation. From [2.11] we obtain an unbiased capital coefficient a_k using a non-linear estimation - as a_k appears twice in [2.11] and in combination with other parameters - with bootstrapped standard errors. The rationale behind stage two in OP is that capital stock is predetermined in period *t* as investment (the proxy variable) is decided in period *t*-1. Therefore in estimating [2.9], k_{it} is exogenous to θ_{it} (the

[11] In the original Olley and Pakes (1996), a third order polynomial is assumed but any other non-parametric functions (such as the kernel density functions) are equally valid.

productivity shock term) and cannot be affected by productivity. This way, the OP algorithm addresses the simultaneity bias between ω_{it} and k_{it} under the assumption that labour is perfectly flexible (non-dynamic)[12].

2.3.2 Levinsohn and Petrin Algorithm

The second semi-parametric technique is the Levinsohn and Petrin (2003), (LP hereafter). This technique shares many similarities with OP, especially as far as the estimation of a_l is concerned, but it seeks to address a major concern underlying the assumption of strict monotonicity in OP. The monotonicity assumption requires that i_{it} is strictly increasing in ω_{it}, which might not hold in practice when there are missing investment values or a significant number of zero investment values in the data. Therefore, the empirical validity of the monotonicity assumption in OP depends on the data series in use, which might be proved problematic for the FAME data that commonly reports missing values for various variables. LP tackles this limitation employing intermediate inputs m_{it} as a proxy variable for unobserved productivity instead of i_{it}. Intermediate inputs m_{it} are now expressed as function of capital and productivity, $m_{it} = m\ (\omega_{it}, k_{it})$. Given that the monotonicity condition is satisfied and materials are strictly increasing in ω_{it}, the *m* function can be inverted. Therefore, the first stage equation in LP is:

$$y_{it} = a_l l_{it} + a_m m_{it} + \varphi(k_{it}, m_{it}) + \varepsilon_{i,t} \qquad [0.12]$$

with $\varphi = a_0 + a_k k_{it} + m^{-1}(k_{it}, m_{it})$ where m^{-1} is the inverse intermediate inputs function. In the LP algorithm, gross output is used as measure of y_{it} usually approximated with revenue. It should be noted that the coefficient of the intermediate inputs a_m in LP is estimated in the second state alongside with a_k. Since m_{it} is not orthogonal with respect to θ_{it} - the idiosyncratic shock term in the Markov process of ω_{it} - the LP algorithm instruments m_{it} with m_{it-1}. The second stage in LP estimates the following specification as:

$$y_{it} - \hat{a}_l l_{it} = a_k k_{it} + a_m m_{it} + f(\hat{\phi}_{it-1}(m_{it-1}, k_{it-1}) - a_0 - a_k k_{it-1} - a_m m_{it-1})) + \theta_{it} + \varepsilon_{it} \quad [0.13]$$

[12] A non-dynamic input means that the choice of this input in year *t* does not affect costs and profits in year *t*+1. In other words, within the OP set-up, labour is perfectly adjustable in year *t* and chosen after productivity ω_{it} is observed.

Estimation of [2.13] is implemented within a GMM framework considering the following moment conditions: $\mathrm{E}[k_{it}\theta_{it}]=0$ and $\mathrm{E}[m_{it-1}\theta_{it}]=0$.

2.3.3 Ackerberg, Caves and Fraser Algorithm

Ackerberg Caves and Fraser (2015) (ACF hereafter) suggest the third semi-parametric technique. This procedure allows for a dynamic specification in the choice of labour. In both OP and LP, labour is considered as a perfectly adjustable input, which is estimated in the first stage. ACF view this assumption as too strong and consider a case in which choices of labour also depend on unobserved productivity ω_{it}. This consideration implies that first stage regressions [2.9] and [2.12] suffer from collinearity and identification problems as the distribution of a_l and ω_{it} do not vary from each other. ACF consider that labour is a function of state variables too: $l_{it}=l(\omega_{it},k_{it})$. To identify labour, ACF assume that the firm chooses labour at period *t*-s where 0<s<1. This implies that the firm chooses labour after capital - still determined in period *t*-1 - and before intermediate inputs, which are chosen in period *t*. Therefore, labour is now an element of the demand function for intermediate inputs in period *t*, $m_{it}=m\ (\omega_{it},k_{it},l_{it})$. This function is still invertible as long as *m* is strictly increasing in ω_{it}. The first stage equation in ACF is defined as:

$$y_{it}=\xi(k_{it},m_{it})+\varepsilon_{it} \qquad [0.14]$$

With $\xi=a_0+a_k k_{it}+a_l l+m^{-1}(k_{it},m_{it},l_{it})$ where m^{-1} is the inverse of intermediate inputs function. The first stage estimation in ACF regresses output on a polynomial function of capital, intermediate inputs and labour to net out random noise and (or) measurement errors related to $\varepsilon_{i,t}$, while all production coefficients are recovered in the second stage with the following moment restrictions:

$$\mathrm{E}[k_{it}\theta_{it}]=0 \text{ and } \mathrm{E}[l_{it-1}\theta_{it}]=0 \qquad [0.15]$$

The estimates of a_k, a_l and a_m in the second stage of ACF are derived from GMM relying on the orthogonality conditions in [2.15].

To sum up, the main message from the discussion in this section is that each method deals with a different challenge in estimating the production function. The approach of each methodology relies on different assumptions whose empirical verification is always subject to data scrutiny. For instance, when firms are characterized from substantial technological heterogeneity, the non-parametric TFP index is preferred to parametric estimations (Van Biesebroeck, 2007). [13] On the other hand, when production is subject to variant returns to scale, then capital share cannot be derived as one minus the labour share and a parametric estimation is more appropriate. Among parametric approaches, the GMM-SYS is the most robust estimator to tackle simultaneity bias and measurement errors. Nonetheless, the empirical functionality of GMM-SYS is always under scrutiny for instruments identification. Semi-parametric techniques are designed to address simultaneity bias between unobserved productivity and selection of inputs using two stages estimation.[14] To provide a more concrete guidance regarding the suitability of each methodology, an experimental exercise using simulated data is in order. Nonetheless, semi-parametric algorithms are structural estimators derived from a firm maximizing behavior, in which case the DGP is not as generic as it should have been in any other random economic series; therefore, we prefer to test the empirical performance of these estimators using observational data from UK Manufacturing firms. In what follows, we estimate the production functions using four alternative approaches (GMM-SYS, OP, LP, ACF) and then we derive the associated TFP indices. The fifth TFP index is constructed from a purely non-parametric technique, equation [2.3], without estimating directly parameters of the production inputs.

2.4 The FAME Data

The data refer to UK Manufacturing firms taken from FAME (Bureau Van Dijk). The initial number of firms includes 13062 firms for the period 2004-2011. These firms cover the following NACE Rev.2 codes: 1011-3299. FAME data are extracted from Profit-Loss and Balance sheets. For the second section of the paper we employ data for R&D expenses and foreign sales (exports). There are two main features of the FAME database. First, there is a bias towards large companies; particularly non-exporting ones (Gal, 2010); second, there are missing values in production inputs making production function and TFP estimates sensitive in the way missing values are treated. The second feature is of special relevance for the

[13] In cases of time variant heterogeneity (stochastic heterogeneity), the Stochastic Frontier Approach (SFA) is the appropriate method (see Kumbhakar and Lovell, 2003 for a review).

[14] Wooldridge (2009) provides a technique that estimates a production function similar to those shown in [2.9], [2.11] and [2.14] within one stage GMM framework. Their two main differences between Wooldridge (2009) and the other semi-parametric techniques are outlined in this paper. First, the one stage estimation tends to be more efficient avoiding potential correlation between errors in two steps and second, the one step GMM can produce robust standard errors unlike other semi–parametric techniques that rely on bootstrapped standard errors. Nonetheless, gains from consistency and accuracy of Wooldridge (2009) estimator are coming at a cost of computational intensity (Mollisi and Rovigatti, 2017).

empirical validity of the monotonicity assumption in i_{it} for OP and m_{it} for LP; thus one needs to know whether our TFP estimates vary substantially between those two algorithms.

We measure y_{it} with value added, which is calculated as total sales minus costs of materials and inventories. We convert sales from FAME into real values using a 4-digit NACE industry production price deflator (2005=100) taken from the Office of National Statistics (ONS). Similarly, we deflate material expenditures (*m*) and fixed assets (capital input) with industry invariant material and capital asset deflators (ONS), respectively. We dropped observations with missing output deflators, especially in cases when the industry NACE classification could not match the ONS classification. There are also observations with negative or missing values for sales as firms usually carry forward losses from previous years. We cannot have observations with negative values of output; so we were forced to drop them.

The capital stock is measured using the book value of fixed assets as reported in FAME. Investment, the proxy for unobserved TFP shocks in OP algorithm is derived from rearranging the standard perpetual inventory formula: $i_{it} = k_{it+1} - (1-\delta)k_{it}$, where δ is the rate of physical depreciation taken at the level of 20%. This formula requires value of fixed assets for 2012 for the computation of investment values for 2011. The time series dimension of our panel reaches up to 2011; we extrapolate the 2012 values of fixed assets in order to obtain investment data for 2011. A possible treatment for missing values is imputation (Gal, 2013); nonetheless, we prefer losing information to using imputed values that are essentially artificial data. We prefer imputing missing values with linear interpolation only in the number of employees (labour). After this cleaning process, the resulting data set is an unbalanced panel for the period 2004-2011.[15]

2.5 Production Function Estimates and TFP Measures

Table 1 provides summary statistics for output and inputs.

Table 1: Summary Statistics - UK Manufacturing Firms, 2004-2011

Variable	N	Mean	Std.	Min	Max
y	58469	8.071	1.405	-3.420	16.624
l	67763	4.568	1.343	2.302	11.600
k	92539	7.164	2.083	-0.156	18.683
m	59289	8.962	1.530	-0.972	17.028

N is the number of observations. All variables are specified in logs.

[15] Given the unbalanced sample used, all estimates reported in the paper allow for implicit entry and exit of firms.

Estimates from parametric and semi-parametric estimators are shown in Table 2. The first estimator in Column 1 shows results from the GMM-SYS with the inclusion of y_{it-1} on the right hand side. For comparability, the GMM-SYS estimator maintains the assumption of predetermined capital in year *t* also specified in OP, LP and ACF. The model in column 1 reports test results for serial correlation in the residuals. There is no evidence for AR(2) in the residuals. As expected, the current data series represent high degree of persistence with the estimated coefficient of y_{t-1} to be 0.79, which raises the issue of weak instrumentation in the estimation of the differenced equation (Arrelano and Bond, 1991). To avoid weak instrumentation, we specify lagged values in levels from *t*-2 up to *t*-4 as instruments for the differenced equation. The Sargan test (p-value=0.1386) indicates that the overall instrumentation strategy of the GMM-SYS is valid (i.e. exogeneity of instruments cannot be rejected).

Columns 2-4 show estimates from OP, LP and ACF. Turning to input coefficients, all models point to the existence of decreasing returns as specified by the Wald test, which can be viewed as evidence for the limitation of the index number approach that assumes constant returns to scale. Capital coefficient takes its highest value in the ACF estimation $\hat{k} \approx 0.13$ while $\hat{l}$ is ranged from 0.32 to 0.69. The estimated coefficient of labour is significantly lower in LP relative to OP and ACF indicating that the first stage estimation in LP under-identifies the contribution of labour. On the other hand, OP produces a statistically insignificant capital coefficient. These features in the input estimates for UK manufacturing firms are similar with those obtained in Eberhardt and Helmers (2010) that employ a smaller sample of firms from FAME. Unfortunately, given that sample sizes vary across models in Table 2, we do not provide a diagnostic test that could have served as a measure for the statistical performance of the four alternative estimators. Nonetheless, given the evidence from Monte Carlo experiments in Ackerberg et al. (2015), where ACF is found to be superior to LP[16] and the striking coefficients of *l* in LP and *k* in OP, we could argue that the ACF estimator that treats labour as a dynamic input is the best alternative within the group of semi-parametric estimators.

[16] ACF shows a Mean Square Error (MSE) to be persistently smaller than LP's.

Table 2: Production Function Estimates for UK Manufacturing Firms, 2004-2011

	GMM-SYS	OP	LP	ACF
k_t	0.11*	0.012	0.117***	0.129*
	(0.036)	(0.012)	(0.008)	(0.07)
l_t	0.530***	0.561***	0.325***	0.437**
	(0.060)	(0.011)	(0.016)	(0.036)
y_{t-1}	0.797***			
	(0.033)			
k_{t-1}	0.019			
	(0.048)			
l_{t-1}	-0.209***			
	(0.055)			
Constant	0.655***			
	(0.113)			
Observations	27155	49687	51815	42631
No Firms	6529	9029	9319	6477
Wald test/p value	139.95/0.000	655.4/0.000	687.17/0.000	5.41/0.02
AR(1)/p value	-5.178/0.000			
AR(2)/p value	-0.598/0.549			
Sargan/p value	78.593/0.137			

Notes: Standard Errors in parentheses with * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. GMM-SYS standard errors are clustered robust. The GMM-SYS is the system GMM estimator (Blundell and Bond, 1998) and includes year fixed effects. The instruments included in the differenced equation in GMM-SYS are lagged values of the endogenous variables from *t*-2, *t*-3 and *t*-4. For the equation in levels the instruments used are lagged values of Δy, Δl and Δk for *t*-2, *t*-3 and *t*-4. The Sargan test refers to the orthogonality condition; under the null the instruments used are valid (i.e. uncorrelated with the error term). The Wald test refers to the constant returns to scale hypothesis: $\hat{a}_l + \hat{a}_k = 1$. OP, LP and ACF algorithms are specified with 100 replications.

TFP estimates in Table 3 are derived from [2.3] for TFP_{INDEX} and from: $\hat{\omega}_{it} = y_{it} - \hat{a}_l l_{it} - \hat{a}_k k_{it}$ for models 2-5. Annual averages are shown in Table 3. Levels from TFP_{INDEX} use reference points from hypothetical units (equation [2.3]) so the figures reported are not directly interpretable. Table 3 shows an upward trend for the period 2004-2008 with a co-movement of all different TFP estimates while there is a fall in 2009; the year of the global financial crisis. The lower section in Table 3 shows TFP growth rates; all methods but TFP_{INDEX} produce an identical pattern of TFP growth with a massive deceleration of TFP for 2009 very close to 17%. TFP_{INDEX} shows a positive rate of TFP for 2009 which is unexpected given the consistent growth pattern from the other group of estimates. This result is more likely a symptom of large measurement errors in the data that the index number approach fails to account for.

Table 3: TFP Estimates for UK Manufacturing Firms, 2004-2011

	Levels				
	TFP_{INDEX}	$TFP_{GMM-SYS}$	TFP_{OP}	TFP_{LP}	TFP_{ACF}
2004	-0.599	2.394	5.390	5.701	5.068
2005	-0.469	2.478	5.461	5.768	5.138
2006	-0.445	2.546	5.516	5.820	5.193
2007	-0.411	2.641	5.605	5.908	5.282
2008	-0.395	2.713	5.666	5.971	5.348
2009	-0.308	2.554	5.449	5.750	5.138
2010	-0.293	2.659	5.548	5.851	5.241
2011	-0.276	2.730	5.622	5.930	5.318
Mean	-0.383	2.602	5.538	5.843	5.223
	Growth Rates (%)				
	TFP_{INDEX}	$TFP_{GMM-SYS}$	TFP_{OP}	TFP_{LP}	TFP_{ACF}
2005	14.422	7.037	8.495	8.557	8.593
2006	3.350	4.648	7.503	7.476	7.488
2007	3.611	8.258	10.401	10.623	10.406
2008	2.455	9.312	7.629	8.074	8.100
2009	7.841	-15.133	-17.772	-17.943	-17.376
2010	2.345	8.084	10.287	10.690	10.742
2011	-0.741	4.561	5.700	6.244	5.971
Mean	4.273	3.804	4.583	4.820	4.842

Table 4 shows spearman correlation between the TFP estimates considered in the paper. Not surprisingly, correlation between all three semi-parametric approaches is high, above 0.90; and it is also high between these three and $TFP_{GMM-SYS}$. The degree of correlation is lower between TFP_{INDEX} and the other approaches, reflecting that the index number is a pure Divisia index without representing any structural micro behavior in the DGP. To address more formally the hypothesis that 2009 is a recession year that is sourced in the global financial crisis, we regress each of these five TFP indices on a set of year dummies. Those results are shown in Table 5. There are considerable differences in the estimated coefficients of year dummies among TFP measures. The year dummy coefficients are smaller in TFP_{OP}, TFP_{LP} and TFP_{ACF} while they tend to be larger in TFP_{INDEX} and $TFP_{GMM-SYS}$. Table 4 reveals a distinct pattern of lower TFP that can be as high as 29% if the Tőrnqvist TFP_{INDEX} is considered. The semi-parametric algorithms indicate a fall in TFP in 2009 between 5 to 7%. Considering these estimates the 2009 global financial crisis has undoubtedly caused negative effects on TFP of UK Manufacturing firms regardless of the way it is measured; nevertheless the size of this effect might vary across TFP estimates.

Table 4: Correlation Matrix of Different TFP Measures

	Model 1	Model 2	Model 3	Model 4	Model 5
	TFP_{INDEX}	$TFP_{GMM\text{-}SYS}$	TFP_{OP}	TFP_{LP}	TFP_{ACF}
TFP_{INDEX}	1				
TFP_{GMM}	0.457	1			
TFP_{OP}	0.390	0.800	1		
TFP_{LP}	0.426	0.776	0.977	1	
TFP_{ACF}	0.526	0.805	0.985	0.987	1

Notes: Spearman Correlations

Table 5: OLS Results from Five Different TFP Measures on Year Dummies, UK Manufacturing Firms

	TFP_{INDEX}	$TFP_{GMM\text{-}SYS}$	TFP_{OP}	TFP_{LP}	TFP_{ACF}
year=2005	0.130***	0.066***	0.071***	0.067***	0.070***
	(5.31)	(4.30)	(3.88)	(3.54)	(3.96)
year=2006	0.154***	0.104***	0.126***	0.119***	0.125***
	(6.34)	(6.92)	(6.97)	(6.36)	(7.14)
year=2007	0.288***	0.290***	0.215***	0.207***	0.214***
	(7.75)	(12.91)	(12.21)	(11.33)	(12.53)
year=2008	0.204***	0.276***	0.276***	0.270***	0.280***
	(8.41)	(18.87)	(15.73)	(14.84)	(16.40)
year=2009	-0.291***	-0.130***	-0.060***	-0.049***	-0.070***
	(12.44)	(8.94)	(3.45)	(2.77)	(4.22)
year=2010	0.306***	0.216***	0.157***	0.150***	0.172***
	(13.19)	(15.14)	(9.35)	(8.60)	(10.51)
year=2011	0.323***	0.291***	0.212***	0.229***	0.200***
	(14.07)	(20.82)	(14.02)	(13.30)	(15.48)
Constant	-0.599***	1.724***	5.390***	5.701***	5.068***
	(34.12)	(154.74)	(406.90)	(414.24)	(393.98)
Observations	51818	51815	51818	51818	51818
R-square	0.006	0.014	0.009	0.008	0.010
F-statistic	43.482	107.550	66.411	61.350	73.520

Notes: Absolute t-statistics in parentheses calculated consistently for robust standard errors and *indicates p< 0.10, **indicates p< 0.05, ***indicates p< 0.01. Each column measures TFP using a different approach, see the text for further details.

3. Evaluate the role of fiscal policy on TFP Growth

3.1 A TFP Catch-Up Model with Corporate Tax

Building on the previous section, we now turn into a more structural model investigating the distortionary effects of taxation on firm TFP. As already pointed out there are two mechanisms first higher corporate tax increases the user cost of capital and second higher taxation liabilities increases financial constraints due to moral hazard and asymmetric information between external creditors and the firm. In both mechanisms, higher corporate tax liability reduces productivity enhancement investment which results in a deceleration in the rate of TFP. We investigate the validity of this hypothesis within a TFP catch-up model (Bernard and Jones, 1996a and 1996b). Accordingly, the evolution of TFP follows an Autoregressive Distributed Lag ADL (1, 1) process with the augmentation of a term that stands for TFP in the frontier *F*:

$$\ln TFP_{it} = \pi_{it} + \alpha_1 \ln TFP_{it-1} + \alpha_2 \ln TFP_{Ft} + \alpha_3 \ln TFP_{Ft-1} + u_{it} \qquad [0.16]$$

Long–run homogeneity in [3.1] $\frac{\alpha_2 + \alpha_3}{1 - \alpha_1} = 1$ implies that productivity growth depends on relative rather than on absolute convergence, which leads to an Error Correction Model (ECM):

$$\Delta \ln TFP_{it} = \alpha_2 \Delta \ln TFP_{Ft} + \pi_{it} + \lambda \ln\left(\frac{TFP_{Ft-1}}{TFP_{it-1}}\right) + u_{it} \qquad [0.17]$$

with $\lambda = 1 - \alpha_1$. Equation [3.2] describes TFP growth in the non-frontier *i* as a function of the autonomous TFP growth in the frontier *F*, a vector of firm specific characteristics π_{it} and a term of technology transfer from *F* to *i*. We define the frontier *F* as $\max TFP_{jt}$, the firm with the highest TFP in industry *j* at year *t*. Vector π_{it} includes:

$$\pi_{it} = \left(T_{it}, R\,\&\,D_i, Export_i\right) \qquad [0.18]$$

where *T* refers to corporate tax liability calculated from the existing statutory tax rate applied for different levels of firm profitability while *R* and *E* are binary variables that denote whether firm *i* is R&D and Export active. Parameter λ shows the speed of productivity convergence between *i* and F; u is a stochastic error term. To test whether the effect of corporate tax on $\Delta \ln TFP_{it}$ varies with firm *i*'s distance from the frontier, we augment equation [3.2] with an interaction term:

$$\Delta \ln TFP_{it} = \alpha_2 \Delta \ln TFP_{Ft} + \pi_{it} + \lambda \ln\left(\frac{TFP_{Ft-1}}{TFP_{it-1}}\right) + \mu Tax_{it} \times \ln\left(\frac{TFP_{Ft-1}}{TFP_{it-1}}\right) + u_{it} \quad [0.19]$$

with μ to capture whether corporate tax liability affects the TFP catch-up process in *i*.[17] Based on our previous discussion, we estimate [3.2] and [3.4] measuring TFP with the ACF algorithm. ACF estimation provides the most meaningful coefficients of capital and labour for the sample of UK manufacturing firms in the presence of selection bias. As a robustness check, we also provide results from $TFP_{GMM\text{-}SYS}$ (Appendix 4). Given that TFP_{ACF}, TFP_{OP} and TFP_{LP} are highly correlated as shown in Table 4, results for [3.2] and [3.4] are not expected to vary substantially when TFP_{OP} and TFP_{LP} are employed.[18]

3.2 Definition of Tax, R&D and Export Variables

The profit-loss accounts in FAME report the corporate tax bill for each *i*.[19] To capture the notion of Effective Marginal Tax Rate (EMTR) (Dwenger, 2014) and how this affects the user cost of capital we use the different statutory tax rate applied for firms of different size (as measured by the levels of profits). Therefore, the benchmark measure of Corporate Tax Liability (*T*) is:

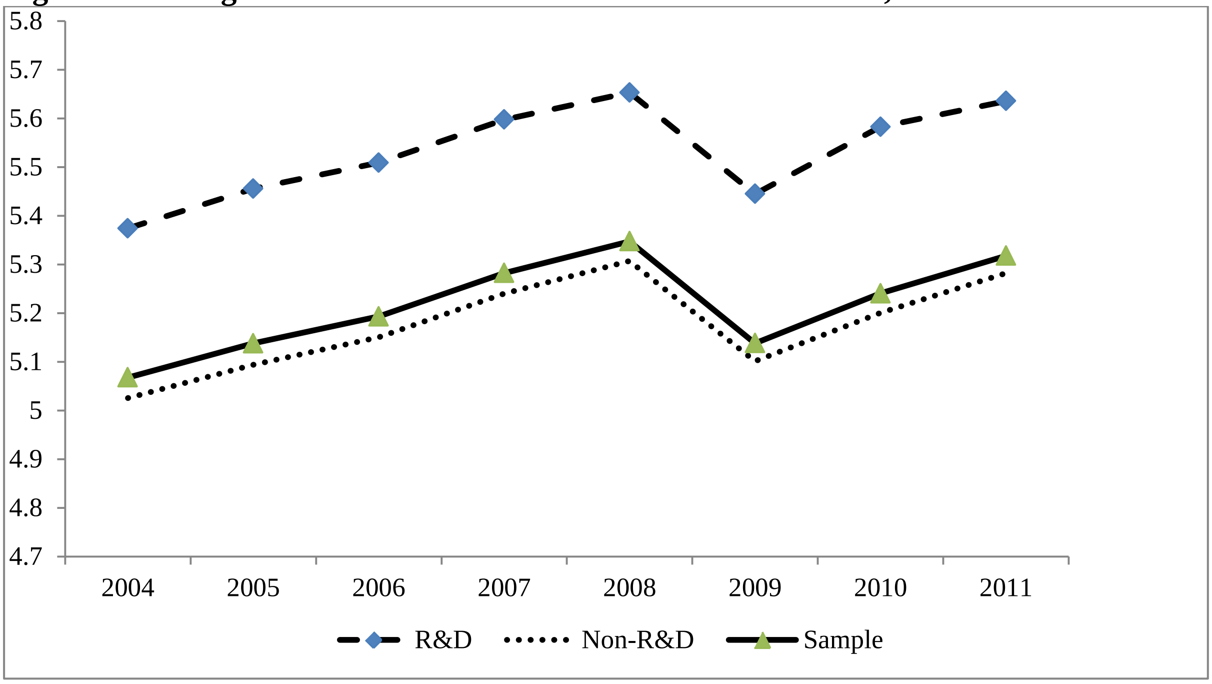
$$T_{it} = \frac{\sum_{s=1}^{5} (EBIT_{it} - \mathrm{M}_s) \times \tau_{ts}}{EBIT_{it}} \quad [0.20]$$

Where *EBIT* is Earnings Before Interest and Taxes as reported in FAME, M is the size threshold for which the statutory tax rate changes and τ is the statutory tax rate (Appendix 2) for firm size *s* in year *t*.[20] The statutory tax rate might change little over time for some group of firms but for small and very large sized firms there are substantial changes in the period under study. Summary statistics for *T* are shown in Appendix 3.

[17] Excluding the corporate tax variable, equation [3.4] is similar to the productivity convergence model of Griffith et al. (2009).
[18] Results of [3.2] and [3.4] for TFP estimates derived from OP and LP are not reported here to save space; they are available from the authors upon request.
[19] Despite having a much lower statutory rate than most G7 countries, the UK raises substantial revenue from corporation tax, typically as much or more (proportionally to GDP) as other G7 countries (Devereux and Loretz, 2011). However, the distribution of payments across companies is highly skewed, with 1 percent of companies contributing about 80 percent of total revenue.
[20] We drop observations with zero or negative EBIT values following Devereux and Loretz (2011).

R&D and exports are binary variables taking value 1 if firm *i* is R&D (export) active and 0 otherwise. We count as R&D active firms those with R&D expenditure data in balance sheets for all eight years of the period 2004-2011. This definition might cause a downward bias for the number of R&D active firms but we prefer focusing on established R&D firms to including firms that occasionally report R&D expenditure for tax relief. Likewise, we use a "strict" definition for exporters assigning value 1 only to continuous exporters (i.e. firms with export data for all 8 years of the sample period).[21] Figures 1 and 2 show the superiority in TFP_{ACF} for R&D and exporting firms, in line with the evidence in other countries that R&D activity matters for TFP (see Bengoa et al., 2017). The TFP level of these firms over the period, 2004-2011, is clearly above the sample average, which also implies that these groups of firms might also be subject to a higher tax bill due to higher levels of profitability

Figure 1: Average TFP Levels of R&D and Non-R&D UK Firms, 2004-2011



[21] We experiment with sporadic exporters too, firms with exports for at least four years (half of the sample). Econometric estimates for the coefficient of export dummies when E=1 also include sporadic exporters and tend to be higher; those results are not shown in the paper but they are available from the authors upon request.

Figure 2: Average TFP Levels of Exporters and Non-Exporters UK Firms, 2004-2011

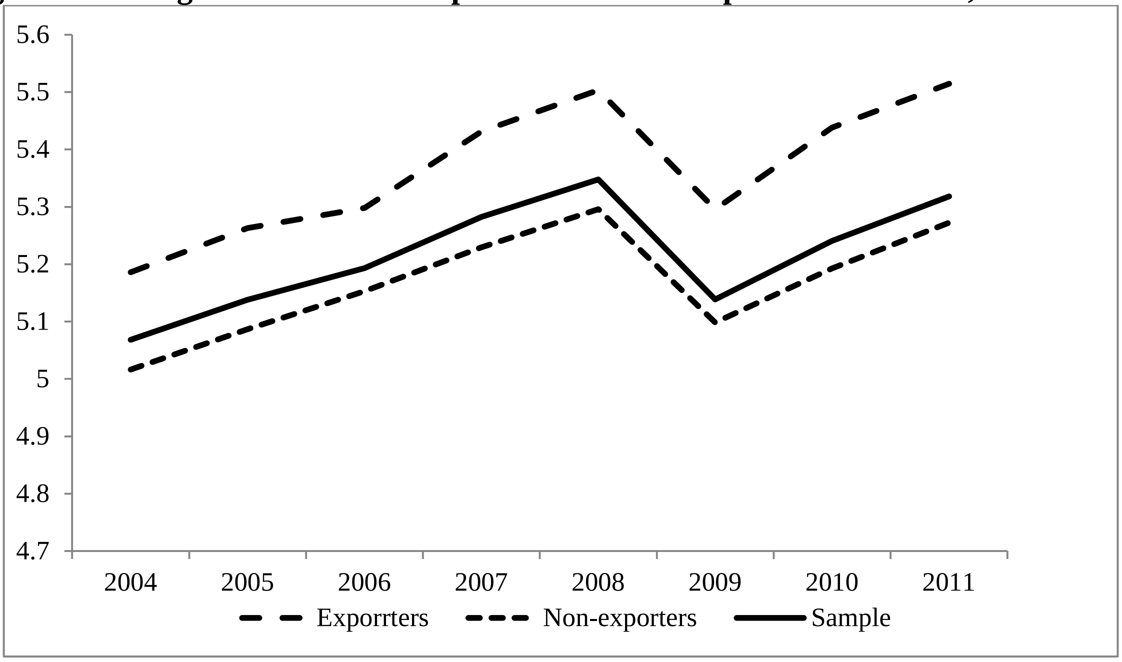
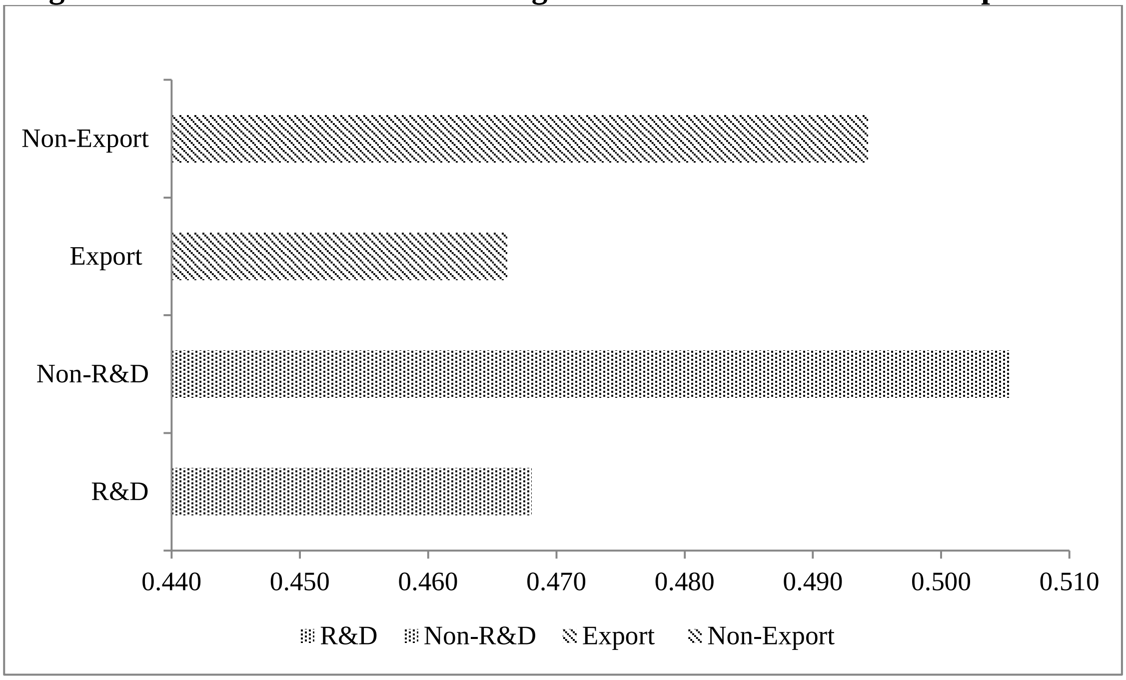


Figure 3 compares the distance from the TFP_{ACF} frontier for R&D and exporting firms versus the inactive groups. On average, R&D and export active firms have a smaller distance to the frontier. Note the time span is short relative to standard macro panel data series; so Figure 3 might not capture in full the dynamics of the convergence process, which implies that these differences are likely to be larger for the sample of UK manufacturing firms. Nonetheless, this descriptive evidence indicates that there are persistent TFP differentials between groups of firms that are exposed to a different degree of risk. The latter indication also raises the issue whether TFP between groups responds differently after changes in tax policy.

Figure 3: Distance from the Technological Frontier for Different Groups



Note: Distance is calculated as 1- $\exp\left(\frac{TFP_{it-1}}{TFP_{Ft-1}}\right)$ with F to be the firm with highest value of TFP_{ACF} in industry *j* at year *t*.

3.3 Econometric Estimation and Results for R&D and Exporters

We proceed with the estimation of [3.2] after adding year and sector (four-digit NACE (Rev2)) fixed effects to capture common macroeconomic shocks and fixed idiosyncrasies at the industry level. For the ease of exposition, we define $GAP_{it-1} = \frac{TFP_{it-1}}{TFP_{Ft-1}}$ and we posit a negative coefficient showing that laggard firms tend to grow faster. Specification [3.4] with the interaction term inclusive assesses whether corporate tax affects the speed of technological catch-up. It follows from the above that a positive $\hat{\mu}$ is expected, representing the distortionary character of *T* in the process of productivity convergence between *i* and *F*. Using OLS to estimate [3.2] and [3.4] is problematic due to endogeneity between $\Delta \ln TFP_{it}$, GAP and *T*. In principle, each firm of the same (or very similar) size faces a common-exogenously determined- corporate statutory tax rate. Nevertheless, if firms experience higher rates of $\Delta \ln TFP$, the tax liability also increases without necessarily reflecting anything behavioral about the distortionary effect of taxation on productivity growth. In other words, $\Delta \ln TFP_{it}$ and tax liability have causal effects - $Cov[Tax_i, u_i] \neq 0$ - so OLS estimates are biased. To address endogeneity bias,[22] we employ GMM considering industry aggregates as potential instruments. This identification strategy relies on the assumption that errors are largely idiosyncratic to the firm but remain uncorrelated to industry aggregate values (Fisman and Svensson, 2007). In that sense, individual firms may blame the high tax burden for their lower rates of $\Delta \ln TFP_{it}$ but it is less likely that all firms in the industry will engage in such blame shifting (Ayyagari et al., 2008). This gives us a good reasoning to argue that causality runs from industry level aggregation to individual firms and not vice-versa. We select as instruments the values in periods *t*-2 and *t*-3 of the following industry aggregate variables: tax liability, equity, profit rate and TFP[23]. We assess the validity of this identification strategy with the orthogonality condition Sargan test, $E\left[Z_i \mid u_i\right] = 0$, where Z is the set of instruments. We also report the Anderson LM test for under-identification, $Cov[Z_i, Tax] \neq 0$. The latter test rejects the null hypothesis that the excluded instruments are relevant; so the equation is under-identified while the Sargan test of instrument validity fails to reject the null about instruments' exogeneity. Overall, this evidence supports the choice of industry aggregates as instruments for the endogenous variables in specifications [3.2] and [3.4].[24]

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[22] IV estimators are also advisable when variables are "noisy", which is often the case for firm level TFP. The semi-parametric calculations of TFP account for simultaneity bias between inputs and productivity, although there are still some unresolved issues such as the degree of capital utilization that might lead to measurement errors. Capital is not always fully utilized introducing short-term variations that do not always reflect technical change.

[23] Equity is defined as the ratio of total assets minus long run liabilities over total assets, while profit rate is the ratio of operational profit to total sales.

[24] We also consider an alternative method of instrumentation using as instruments higher order lags of the endogenous variables. Although, these instruments pass the under-identification test they fail to satisfy the orthogonality condition of the Sargan test.

Table 6: GMM Estimates of a TFP Catch Up Model with Tax Liability, UK Firms 2004-2011

	Full Sample	Full Sample	R&D	Non-R&D	Exporters	Non-Exporters
$\Delta \ln TFP_F$	0.571***	0.298***	0.276**	0.237***	0.267***	0.145***
	(6.53)	(8.38)	(2.15)	(6.08)	(4.67)	(3.94)
GAP	-0.614***	-0.757***	-0.572	-0.404***	-0.225***	-0.046***
	(5.46)	(8.36)	(1.08)	(6.01)	(4.59)	(3.84)
T_{t-1}	-0.650***	-0.486***	-0.236***	-0.851	-0.486**	-0.285
	(9.08)	(5.50)	(2.74)	(0.41)	(2.53)	(1.09)
$(GAP \times T)_{t-1}$		4.206***	1.929*	1.244**	4.714	10.061
		(5.35)	(1.70)	(2.12)	(0.32)	(0.82)
R&D	0.261***	0.039			0.444***	0.428***
	(5.34)	(0.36)			(3.32)	(2.95)
Export	0.090***	0.014	-0.029	0.154***		
	(4.64)	(0.36)	(1.03)	(4.27)		
Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	31812	36946	4330	32616	25147	11799
Anderson LM	31.438	11.726	4.073	20.427	11.121	8.331
p value	0.000	0.003	0.254	0.000	0.011	0.040
Sargan	3.229	3.215	2.704	1.87	1.286	3.889
p value	0.199	0.173	0.254	0.351	0.14	0.189

Notes: Absolute t-statistics in parentheses calculated consistently for robust standard errors clustered by firm and *indicates p< 0.10, **indicates p< 0.05, ***indicates p< 0.01. TFP calculations are derived from the Ackerberg et al.,2015 algorithm. The instruments in all specifications are industry aggregates of *T*, profit rate, equity and TFP at the NACE Rev 2 level in periods t-2 and t-3. The Sargan test refers to the orthogonality condition; under the null the instruments used are valid (i.e. uncorrelated with the error term. The Anderson LM test refers to the relevance of instruments with the endogenous variable; under the null the set of instruments used is weak. GAP stands for the TFP distance of a given firm from the industry frontier. *T* refers to the tax due by the firm according to the relevant tax rate for each specific year during the sample. R&D is a dummy variable taking the value one if a firm is research active (report R&D expenditures for all years of the sample) and zero otherwise. Export is a dummy variable taking the value one if a firm is an exporter for all the years of the sample and zero otherwise

Table 6 reports GMM results. Column 1 shows estimates from specification [3.2]. The effect of industry frontier's TFP growth is positive signifying the existence of positive spillovers initiated from more productive firms in the industry. A 1% increase in the TFP growth of *F* increases growth rate in *i* by 0.57 percentage points. The coefficient of *GAP* is negative and highly significant confirming the hypothesis that TFP of laggard firms tend to experience faster TFP growth rates. More importantly, the effect of corporate tax liability on $\Delta \ln TFP_{it}$ is negative and significant in statistical terms. A 1% increase in *T* decreases $\Delta \ln TFP_{it}$ by 0.65 percentage points. The size of this effect is larger to what Gemmell et al. (2016) documented for a larger number of OECD countries. R&D and exporting firms experience higher growth of TFP, which is evidence that risk taking activities are associated with better productivity performance. In column (2), we show results for specification [3.4] which includes the interaction term $[GAP \times Tax]_{t-1}$. The coefficient of the interaction term is positive and statistically significant implying that the pace of TFP convergence decelerates with higher levels of tax liability.

Columns (3) to (6) examine whether the role of corporate tax varies between groups of firms with reference to their R&D and export status. We first distinguish between R&D and non-R&D firms. The GAP term is insignificant in the former group signifying that firms engaged into innovation are already very close to the frontier; so gains from convergence towards the frontier are limited. The tax coefficient remains negative and statistically significant for the group of R&D firms while it is now insignificant for the non-R&D group. The interaction term $[GAP \times Tax]_{t-1}$ for the group of R&D firms is significant only at the 10% level with a much smaller coefficient compared to the one in the full sample of firms. This is a key difference between firms that undertake R&D projects and are exposed to higher degree of uncertainty. The higher level of tax liability weakens the borrowing capacity of firms that invest in innovation which can potentially discourage the generation of new knowledge (see for example Bournakis et al., 2017). A similar effect is also revealed when we split the sample between exporters and non-exporters, columns (5) and (6). The higher level of tax liability impacts negatively on the group of exporters while the group of non-exporters is unaffected. Column (5) also indicates that the rate of TFP convergence for exporters is also driven from tax liability. Likewise, with R&D firms, corporate tax generates credit constraints that impede international market expansion of export oriented firms. Overall, results in Table 5 clearly suggest that corporate tax causes distortionary effects on productivity and these effects are not driven from endogeneity bias between *T*, GAP and $\Delta \ln TFP_{it}$. A similar outcome holds for the negative repercussions of higher tax levels on convergence towards the frontier for the R&D group.

A further sensitivity test is to investigate whether results shown in Table 5 are robust to an alternative definition of the tax variable. The tax liability variable defined in [3.5] represents what a firm is ought to pay without capturing firm's efforts to shift the amount of tax bill on the pre-tax profits.[25] To see the actual amount of tax paid we use a tax definition closer to the concept of the Effective Average Tax Rate (EATR). [26] Our second tax measure

[25] Devereux and Lorenz (2011) note that it is common to expect firms with different ownership status to alter the real value of EBIT purely for tax relief purposes.

[26] We refer to Devereux and Griffith (1999, 2002, and 2003) and Simmler (2012) for more sophisticated definitions of Effective Average Tax Rate (EATR). Despite its simplicity our ETR variables is a transparent and adequate measure in capturing what a profit maximizing entrepreneur considers when making investment decisions (Djankov et al. 2008).

is the Effective Tax Rate (ETR) using information only from FAME and it is defined as the share of Corporate Tax to *EBIT*. We replicate GMM estimations of [3.2] and [3.4] with the same instrument identification strategy as in Table 6 with ETR. Results are shown in Table 7. In the full sample, the size of the ETR effect on $\Delta \ln TFP_{it}$ is somehow smaller, 0.30, which already reflects productivity benefits from the lower ETR paid.[27] The same applies for the effect of ETR on the TFP convergence process, which is now significant only at the 10% level and almost half of the size of the coefficient $(GAP \times T)_{t-1}$. The autonomous effect of ETR for different groups reinforces our previous results that the risk taking groups are more severely affected from a higher level of corporate tax. It should be noted that the size of the ETR coefficient in column (3) is much higher than the coefficient of *T*. Overall, there are two qualifying messages for the results shown in Tables 5 and 6. First, higher corporate tax payments aggravate capital investment decisions mainly by reducing the amount of working capital, which is the main asset that firms can use to secure external funding. Second, there is disproportionate effect of corporate tax on firms that are more dependent on external finance and exposed at higher risk such as R&D and exporting. [28]

[27] The sample average for ETR is 12.6% as a share to Taxable profit while for *T* is 16.2%.

[28] We also run additional set of robustness checks with F to be defined as the 5% of firms with the highest TFP in the industry at year t and the firm with the highest TFP across all industries in year t. Our results remain robust with regard to the distortionary effect of tax liability and its effect on the convergence process of laggard firms. Finally, we reproduce estimates of [3.2] and [3.4] with the GMM-SYS methodology of measuring TFP, results are shown in the Appendix 4. The message of Tables 5 and 6 prevails. The only remarkable difference between Tables 5 and 6 and Appendix 4 is that the distortionary effect of tax liability is now present in the non-exporting group as well.

Table 7: GMM Estimates of a TFP Catch Up Model with Effective Tax Rate (ETR), UK Firms 2004-2011

	Full Sample	Full Sample	R&D	Non-R&D	Exporters	Non-Exporters
$\Delta \ln TFP_F$	0.315***	0.755***	0.389	0.665**	0.75***	0.699**
	(6.20)	(3.16)	(1.17)	(2.34)	(4.12)	(2.44)
GAP	-0.310***	-0.870***	-0.594	-0.736**	-0.867***	-0.790**
	(4.33)	(2.87)	(1.40)	(2.02)	(4.05)	(2.13)
ETR_{t-1}	-0.308**	-0.47*	-0.79***	-0.052	-0.301***	-2.909
	(2.52)	(1.88)	(3.46)	(1.35)	(3.55)	(1.30)
$(GAP \times ETR)_{t-1}$		2.281*	-1.159	3.418	0.512***	3.239
		(1.72)	(0.24)	(1.17)	(3.62)	(1.12)
R&D	0.001	0.002			-0.017	0.001
	(0.09)	(0.27)			(1.06)	(0.05)
Export	0.004	0.003	0.007	0.008		
	(0.70)	(0.35)	(0.40)	(0.93)		
Industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	30568	30557	3518	27039	7393	23164
Anderson LM	1013.143	65.012	30.112	51.763	26.588	52.528
p value	0.000	0.000	0.001	0.000	0.000	0.000
Sargan	7.272	8.143	13.756	9.273	2.549	2.107
p value	0.12	0.163	0.131	0.331	0.863	0.71

Notes: Absolute t-statistics in parentheses calculated consistently for robust standard errors clustered by firm and *indicates p< 0.10, **indicates p< 0.05, ***indicates p< 0.01. TFP calculations are derived from the Ackerberg et al., 2015 algorithm. The instruments in all specifications are the average values of TFP, ETR, profit rate, equity at the NACE Rev. 2 industry level in periods t-2 and t-3. The Sargan test refers to the orthogonality condition; under the null the instruments used are valid (i.e. uncorrelated with the error term. The Anderson LM test refers to the relevance of instruments with the endogenous variable; under the null the set of instruments used is weak. GAP stands for the distance of productivity of a given firm from the industry frontier. ETR is the ratio of corporate tax over EBIT. R&D is a dummy variable taking the value one if a firm is research active (report R&D expenditures for all years of the sample) and zero otherwise. Export is a dummy variable taking the value one if a firm is an exporter for all the years of the sample and zero otherwise

4. Conclusions

This paper has provided a methodological overview of TFP estimation for UK Manufacturing firms over the period 2004-2011. The first part of the paper explored the limitations and merits of existing methodologies arguing that TFP computation in empirical studies should not be treated as a mechanical issue or of secondary importance. Indeed, our empirical experiment in Table 5 shows that the effect of the global financial crisis in 2009 on productivity varies depending on the TFP method chosen. Our estimations show that the methodology of Ackerberg et al. (2015) treats labour as a dynamic input whose choice affects future profits providing the most plausible estimates for capital and labour inputs. The semi-parametric techniques of Olley and Pakes (1996) produce a statistically insignificant estimate of capital which is controversial, while the Levinsohn and Petrin (2003) approach produces an unexpectedly low estimate for labor. Only the ACF methodology provides results that can be regarded as in line with the macro growth accounting literature. The use of non-parametric techniques appeared to be the least suitable for firm level estimations of TFP as it fails to control for measurement error that is usually present in the data. The GMM-SYS estimator is the second best option after the ACF estimator. This approach controls for the standard simultaneity bias between unobserved productivity and selection of inputs, while it also corrects for measurement error, with the only caveat concerning GMM-SYS that instrument identification is always subject to empirical scrutiny depending on the dataset in use.

The second part of the paper uses a more structural approach to analyse the impact of corporate taxation on productivity within a TFP catch-up framework. We contribute to the limited body of micro-evidence in the tax-productivity domain. Evidence shown in the paper suggests that higher rates of corporate taxation slow down the rate of TFP growth. This finding remains robust regardless of the way we derive TFP. There are quantitative differences in the size of this effect depending on the TFP estimation used but higher corporate tax payments always affect productivity enhancing investment that decelerate the growth of TFP. This effect is higher for firms with higher exposure to risk and those who are more financially constrained. Our findings provide evidence in favour of theoretical models that highlight the importance of asymmetric information and moral hazard in the allocation of external funds. A policy message from the present study is that the design and reform of any tax system should be tolerant to firms that undertake risk. The activities of these firms usually generate substantial knowledge returns that bring beneficial productivity spillovers to the rest of the economy.

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APPENDICES

Appendix 1: Description of Variables

Name	Definition
y	Total Sales in logs adjusted for the cost of materials and firm inventories converted to real values using 4-digit NACE industry specific PPI
k	Total fixed assets in logs converted into real values with an industry invariant capital price index taken from ONS.
l	Number of Employees
m	Cost of Materials in logs converted into real values with an industry invariant material price index taken from ONS.
T	Tax Liability as defined in Equation [3.5]
τ	Statutory Tax Rate, taken from Devereux and Loretz (2011)
Taxable Profit	Profits before Tax (PbT)
ETR	The ratio of Corporate Taxation over *EBIT*
EBIT	Earnings before Income and Tax, variable reported as operating Profit
R&D	R&D=1 if firm reports R&D Expenditures for all 8 years and 0 otherwise.
Export	**Continuous Exporter**: *Export*=1 if firm reports turnover for overseas sales for all 8 years and 0 otherwise. **Sporadic Exporter**: *Export*=1 if firm reports turnover for overseas sales for at least 4 years and 0 otherwise.
Industry Profit Rate	Operational profit over total sales, average values across NACE Rev2
Industry Equity	(Total Assets – Long Term Liabilities)/ Total Assets

Notes: All data are taken from FAME unless stated otherwise.

Appendix 2: UK Statutory Corporate Tax Rate Schedule

Taxable profit	**2000/01 to 2001/02**	**2002/03 to 2005/06**	**2006/07**	**2007/08**	**2008/09 to 2010/11**
0 to 10,000	10%	0%	19%	20%	21%
10,001 to 50,000	22.5%	23.75%	19%	20%	21%
50,001 to 300,000	20%	19%	19%	20%	21%
300,000 to 1,500,000	32.5%	32.75%	32.75%	32.5%	29.75%
More than 1,500,001	30%	30%	30%	30%	28%

Source: Devereux and Lorenz, 2011

Appendix 3: Tax Liability and Effective Tax Rate (ETR) of UK Firms for Different Percentiles

Year	**Mean**	**Std. Dev.**	**p50**	**p75**	**p90**
		T			
2005	0.160	0.031	0.168	0.190	0.190
2006	0.190	0.001	0.190	0.190	0.190
2007	0.200	0.000	0.200	0.200	0.200
2008	0.210	0.000	0.210	0.210	0.210
2009	0.210	0.000	0.210	0.210	0.210
2010	0.210	0.000	0.210	0.210	0.210
2011	0.200	0.000	0.200	0.200	0.200
Average	0.203	0.008	0.210	0.210	0.210
		ETR			
2004	0.162	0.146	0.149	0.263	0.383
2005	0.158	0.146	0.144	0.265	0.375
2006	0.159	0.148	0.144	0.266	0.385
2007	0.157	0.147	0.140	0.264	0.374
2008	0.158	0.150	0.139	0.266	0.391
2009	0.153	0.148	0.132	0.260	0.380
2010	0.141	0.138	0.123	0.241	0.325
2011	0.130	0.128	0.114	0.220	0.290
Average	0.151	0.144	0.134	0.252	0.359

Appendix 4: Estimates from a TFP Catch Up Model, Specifications [3.2] and [3.4] with $TFP_{GMM\text{-}SYS}$, UK Firms 2004-2011

	Full Sample	Full Sample	R&D	Non-R&D	Exporters	Non-Exporters
$\Delta lnTFP_F$	1.226***	1.122***	-0.065	1.124***	0.508	1.749***
	(18.09)	(4.89)	(0.06)	(5.17)	(1.44)	(5.18)
GAP	-2.435***	-2.228***	0.356	-0.235***	-0.963	-0.428***
	(16.28)	(4.88)	(0.16)	(5.14)	(1.37)	(5.14)
Tax_{t-1}	-0.408***	-0.168**	-0.459***	0.121	-0.170**	-0.048**
	(6.45)	(2.13)	(3.04)	(0.10)	(2.04)	(1.98)
$(GAP\times T)_{t-1}$		1.136	0.088	0.938**	0.907**	0.852*
		(0.46)	(1.19)	(2.40)	(2.20)	(1.71)
R&D	0.127***	0.128***			0.122***	0.149***
	(10.78)	(10.72)			(7.62)	(7.58)
Export	0.026***	0.026***	0.016	0.028***		
	(3.86)	(3.87)	(0.69)	(4.04)		
Industry Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	36943	36943	4330	32613	19001	17942
Anderson LM	322.102	211.625	12.163	214.672	78.662	112.564
p value	0.000	0.000	0.007	0.000	0.000	0.000
Sargan	2.585	2.760	5.374	1.084	2.678	0.077
p value	0.108	0.097	0.068	0.298	0.102	0.781

Notes: Absolute t-statistics in parentheses calculated consistently for robust standard errors clustered by firm and *indicates $p< 0.10$, **indicates $p< 0.05$, ***indicates $p< 0.01$. TFP calculations are derived from a parametric GMM-SYS estimation of [2.3]. The instruments in all specifications are industry aggregates of *T*, profit rate, equity and TFP at the NACE Rev 2 level in periods t-2 and t-3. The Sargan test refers to the orthogonality condition; under the null the instruments used are valid (i.e. uncorrelated with the error term. The Anderson LM test refers to the relevance of instruments with the endogenous variable; under the null the set of instruments used is weak. GAP stands for the TFP distance of a given firm from the industry frontier. *T* refers to the tax due by the firm according to the relevant tax rate for each specific year during the sample. R&D is a dummy variable taking the value one if a firm is research active (report R&D expenditures for all years of the sample) and zero otherwise. Export is a dummy variable taking the value one if a firm is an exporter for all the years of the sample and zero otherwise