

Technological Catch-up and the Role of Multinationals

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Abstract

This paper examines productivity catch-up as a source of establishment productivity growth. We present evidence that, other things equal, establishments further behind the industry frontier experience faster rates of productivity growth. Our econometric specification implies a long-run relationship between productivity levels, where non-frontier establishments lie a steady-state distance behind the frontier such that their rate of productivity growth including catch-up equals productivity growth at the frontier. We present evidence of the extent to which U.S. multinationals are the highest productivity establishments within industries. We use our econometric estimates to quantify their implied contribution to growth in non-frontier establishments through productivity catch-up.

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1 Introduction

Deregulation and the opening of markets to international trade and investment have been widely recognized as major drivers of growth. Recent studies on entry regulation¹ have revived interest in the subject and foreign firms have been identified as important potential conduits of technology transfer. The existing literature on productivity spillovers from foreign firms typically regresses productivity levels or growth rates on a measure of foreign presence in an industry. But any high productivity establishment within the industry, whether it is foreign or domestically-owned, provides a potential source of productivity catch-up.² Building on this idea, we use a standard time-series econometric specification to provide evidence on the contribution of productivity catch-up to productivity growth in non-frontier establishments. While our framework allows for productivity catch-up to leading establishments of any nationality, we find that US-owned multinationals located in the UK are frequently the most productive establishments within industries and account for a substantial share of manufacturing employment. Using our econometric specification, we quantify their implied contribution to productivity growth in non-frontier establishments through productivity catch-up.

The literature that regresses productivity levels or growth rates on the share of foreign firms in employment, sales or the total number of firms is extensive.³ While much of this research concentrates on productivity spillovers from inward investment, other recent work has emphasized the importance of “technology sourcing” where firms locate abroad in or-

¹See, *inter alia*, Baily *et al.* (1992), Davis and Haltiwanger (1991), Nicoletti and Scarpetta (2002) and Djankov *et al.* (2002).

²For empirical evidence that domestic multinationals frequently have comparable levels of productivity to foreign multinationals, see Doms and Jensen (1998), Girma and Görg (2007), Griffith and Simpson (2004) and Criscuolo and Martin (2005).

³See for example Aitken and Harrison (1999), Blomstrom (1989), Globerman (1979), Görg and Strobl (2001), Keller and Yeaple (2002), Smarzynska Javorcik (2004) and Teece (1977). Work that has looked at this issue in the context of the UK includes Haskel, Pereira and Slaughter (2002), Girma and Wakelin (2000), Görg and Greenaway (2002), and Harris and Robinson (2002).

der to access the latest technologies and repatriate them to their home country.⁴ In both cases, productivity catch-up to high productivity establishments within industries provides a potential source of productivity growth to non-frontier establishments. Our approach incorporates productivity catch-up while at the same time allowing for persistent productivity dispersion within industries. In the long-run relationship implied by our econometric specification, non-frontier establishments lie a steady-state distance behind the frontier such that their rate of productivity growth including catch-up equals productivity growth at the frontier. Our approach thus reconciles productivity heterogeneity, as documented in the micro-econometric literature on firms and plants, with productivity catch-up as emphasized in the macroeconomic literature on convergence.⁵ Our paper contributes to an emerging literature that emphasizes the characteristics of both domestic and foreign firms in influencing the extent to which foreign presence contributes towards domestic productivity growth.⁶

The United Kingdom provides a natural context within which to explore the role of productivity catch-up. Throughout the 1970s productivity levels and growth rates in the UK lagged behind those of the US. The 1980s saw a period of rapid growth in the UK that led to a reduction in the aggregate productivity gap with the US. This aggregate picture hides substantial heterogeneity in productivity across establishments and a Darwinian process of selection as poor performers exited and were replaced by new cohorts of establishments. The 1970s and 1980s were also a time when the British economy was becoming increasingly open to international competition. By 1980 the British government had removed exchange controls and had joined the European Economic Community. By the late 1980s Britain was

⁴Case studies emphasising technology sourcing include von Zedtwitz and Gassman (2002) or Serapio and Dalton (1999) and the references therein. Econometric evidence is contained in Griffith, Harrison and Van Reenen (2006) and Branstetter (2004).

⁵The micro-econometric literature includes Baily *et al.* (1992), Bartelsman and Doms (2000), Davis and Haltiwanger (1991), Davis, Haltiwanger and Schuh (1996), Disney *et al.* (2003), Dunne, Roberts and Samuelson (1989) and Foster, Haltiwanger and Krizan (2002) among others. For macroeconomic research on productivity convergence, see Acemoglu *et al.* (2002), Aghion and Howitt (1997), Cameron (1996), Cameron *et al.* (2005), Grossman and Helpman (1991), Howitt (2000) and Parente and Prescott (1994, 1999).

⁶See for example Girma, Greenaway and Wakelin (2001), Girma (2005), and Kinoshita (2001).

embarking on the EU Single Market Program which aimed to improve the international mobility of factors including capital. This opening up of the UK economy was expected to increase growth through a number of routes, including technology transfer from more advanced economies, facilitated by the presence and entry of foreign-owned multinationals employing superior production techniques within the UK.

The structure of the paper is as follows. Section 2 outlines our empirical approach. Section 3 discusses the data and a number of measurement issues. In section 4 we present our econometric results. First we present our estimates of productivity catch-up before examining the contribution of foreign firms. A final section concludes.

2 Empirical Framework

Our main interest lies in understanding how the distribution of productivity evolves over time and whether we can find evidence consistent with productivity catch-up. We employ a formulation from the macroeconomics literature on convergence (see for example Bernard and Jones 1996 and Cameron 2005), which captures productivity catch-up, but which also encompasses other observed empirical regularities: persistence in productivity levels at the establishment level over time and heterogeneity in productivity levels across establishments. Equation (1) describes our starting point where i indexes establishments and t time. We characterise $\ln A$, an index of technology or Total Factor Productivity (TFP), as a function of it's prior level (A_{it-1}) to capture persistence, an individual specific factor (γ_i) to reflect heterogeneity in innovative capabilities, and the current productivity frontier (A_{Fjt-1}) to capture convergence:

$$\ln A_{it} = \ln A_{it-1} + \gamma_i + \lambda \ln \left(\frac{A_{Fj}}{A_i} \right)_{t-1} + u_{it}. \quad (1)$$

where the parameter γ_i captures an establishment's own rate of innovation through its underlying capabilities; the parameter λ captures the speed of productivity catch-up; and

u_{it} captures the influence of stochastic shocks to productivity growth.

Re-arranging equation (1), taking the first term on the right-hand side over to the left-hand side, we obtain:

$$\Delta \ln A_{it} = \gamma_i + \lambda \ln \left(\frac{A_{Fj}}{A_i} \right)_{t-1} + u_{it} \quad (2)$$

where u_{it} is a stochastic error. While this provides our baseline specification, we also consider a number of generalizations and robustness tests.

We estimate the specification in equation (2) for all non-frontier establishments (section 3.4 discusses how we identify the frontier). We face a number of specific challenges in doing this. The first is obtaining accurate measures of $\Delta \ln A_i$ and $\ln(A_F/A_i)$ and section 3.2 discusses our approach to productivity measurement and the large number of robustness tests that we undertake. The second is that A_{it-1} appears on both the left and right-side of equation (2), so that shocks to A_{it-1} due for example to measurement error could lead to biased estimates of the speed of technological convergence λ . We address this concern in section 4.2 using a variety of approaches including instrumental variables estimation. Third, we need to ensure that identification of λ is being driven by variation in the position of the frontier A_{Fjt-1} , and thus indicates productivity catch-up, and does not simply reflect other phenomena such as mean reversion, as discussed in section 4.4.

A final issue is that we can only estimate equation (2) on surviving establishments. To control for the non-random survival of establishments, we use a standard Heckman (1976) selection correction, estimating a probit regression for firm survival and augmenting the equation for productivity growth in (2) with an inverse mills ratio. We model a firm's exit decision as a function of firm age, investment, capital stock, their interactions and higher-order terms in these variables (see also Pavcnik 2003). Under the assumption of constant returns to scale and Hicks-neutral productivity differences that raise the productivity of all factors by the same proportion, investment, the capital stock, their interactions and

higher-order terms in these variables have no direct impact on productivity.

Our empirical model for productivity growth in equation (2) permits a general specification of the error term. The specification includes an establishment-specific fixed effect (γ_i) that we allow to be correlated with other independent variables. For example, establishments which begin far from the frontier and converge rapidly towards it may be precisely those with high levels of innovative capabilities γ_i . We also include a full set of time dummies, T_t , to control for common shocks to technology and macroeconomic fluctuations, together with an idiosyncratic error, ε_{it} :

$$u_{it} = T_t + \varepsilon_{it}. \quad (3)$$

Standard errors are clustered on four-digit industries, which allows the error term to be correlated in an unrestricted way across time and across establishments within industries (see, for example, Bertrand *et al.* 2004). Clustering on four-digit industries is more demanding than clustering on establishments, since we only assume the error term is independent across industries rather than assuming independence across establishments.

As a robustness test we consider an augmented version of this specification, which allows for a more flexible specification of the relationship between non-frontier and frontier TFP, in the form of an Autoregressive Distributed Lag ADL(1,1) model:

$$\ln A_{it} = \gamma_i + \alpha_1 \ln A_{it-1} + \alpha_2 \ln A_{Ft} + \alpha_3 \ln A_{Ft-1} + T_t + \varepsilon_{it}. \quad (4)$$

We assume long-run homogeneity ($\frac{\alpha_2 + \alpha_3}{1 - \alpha_1} = 1$) so that the rate of productivity catch-up depends on relative, rather than absolute, levels of productivity.⁷ The cointegrating relationship between non-frontier and frontier TFP above therefore has the following Equilibrium Correction Model (ECM) representation, with many attractive statistical properties:⁸

⁷Under this assumption, doubling A_{it-1} , A_{Ft} and A_{Ft-1} doubles A_{it} , ensuring that the rate of productivity catch-up does not depend on units of measurement for output or factor inputs.

⁸See Hendry (1996).

$$\Delta \ln A_{it} = \gamma_i + \beta \Delta \ln A_{Ft} + \lambda \ln \left(\frac{A_{Fj}}{A_i} \right)_{t-1} + T_t + \varepsilon_{it}, \quad (5)$$

where equation (2) is a more restrictive version of this expression, with $\beta = \alpha_2 = 0$ and $\lambda = (1 - \alpha_1)$.

2.1 Implications for productivity dispersion

Before proceeding to discuss the data and presenting our baseline empirical results, it is useful to examine the implications of our empirical framework for the cross-section distribution of productivity within the industry. This is not central to our empirical strategy, but clarifies the interpretation of the results and makes clear how productivity catch-up is consistent with long-run productivity dispersion.

The productivity frontier in industry j advances at a rate determined by innovative capabilities γ_{Fj} and a stochastic error u_{Fjt} :

$$\Delta \ln A_{Fjt} = \gamma_{Fj} + u_{Fjt}. \quad (6)$$

Combining the expression for the frontier above with the equation for TFP growth in a non-frontier establishment i in equation (2), yields an expression for the evolution of productivity in establishment i relative to the industry j frontier:

$$\Delta \ln (A_{it}/A_{Fjt}) = (\gamma_i - \gamma_{Fj}) + \lambda \ln \left(\frac{A_{Fjt-1}}{A_{it-1}} \right) + (u_{it} - u_{Fj}). \quad (7)$$

Taking expectations in equation (7) prior to the realization of the stochastic shock to technology, the error terms are equal to zero and the long-run equilibrium level of productivity relative to the frontier implied by our econometric specification is:

$$\mathbf{E} \ln \left(\frac{\widehat{A_i}}{A_{Fj}} \right) = \frac{\gamma_i - \gamma_{Fj}}{\lambda}. \quad (8)$$

Intuitively, there is productivity dispersion within the industry because establishments differ in their underlying potential to innovate ($\gamma_i \neq \gamma_{Fj}$) and it takes time to converge towards the constantly advancing frontier (λ is finite). In the long-run, the frontier will be whichever establishment in the industry has highest γ_i ($\gamma_{Fj} = \sup_i\{\gamma_i\}$). All other establishments will lie a distance behind the frontier, such that expected productivity growth including catch-up equals expected productivity growth in the frontier.

One of our empirical findings is that the affiliates of US multinationals frequently lie at the industry productivity frontier. In terms of equation (8), this finding implies that affiliates of US multinationals often have higher values of γ_i than other multinationals and than purely domestic establishments. The higher values of γ_i are consistent with fixed costs of becoming a multinational, so that only the most productive foreign firms are observed in the UK, and with the US having technological leadership in a range of industries.

Equations (1), (7) and (8) are most closely related to the time-series literature on convergence, since they imply a long-run cointegrating relationship between TFP in frontier and non-frontier establishments. The inclusion of establishment-specific fixed effects in the econometric specification means that the parameters of interest are identified from the differential time-series variation across establishments in the data. The analysis focuses on the relationship over time between an establishment's rate of growth of productivity and its distance from the frontier.

Although the establishment fixed effects are included in an equation for productivity *growth* (2), the presence of the term in lagged productivity relative to the frontier means that the equation estimated can be interpreted as a dynamic specification for how the *level* of each establishment's productivity evolves relative to the frontier (the equation is an ECM representation of this relationship). Therefore, the fixed effects are capturing information on the steady-state level of each establishment's productivity relative to the frontier, depending on its underlying capabilities, as is revealed by equation (8).

Our approach differs from the literature on β -convergence, which explores the *cross-section* relationship between rates of growth of productivity and initial own levels of productivity in that we include a role for the technology frontier. More specifically, we focus on the *time-series* relationship between an establishment's productivity and productivity at the frontier. Our approach also differs from the literature on σ -convergence, which examines the *evolution of cross-section* measures of dispersion such as the sample standard deviation of productivity. Depending on the relationship between the initial distribution of productivity and the steady-state distribution in equation (8), the cross-section sample standard deviation of productivity may rise, decline or remain constant over time.⁹

In summary, our econometric specification captures heterogeneity in productivity within industries, while allowing for productivity catch-up. Each establishment converges towards its own steady-state level of productivity relative to the industry frontier and there is long-run productivity dispersion.

3 Data and measurement issues

3.1 Measuring growth and relative levels of TFP

As emphasized above, one of the main challenges in the productivity literature is obtaining accurate measures of TFP growth and relative levels ($\Delta \ln A_i$ and $\ln(A_F/A_i)$ respectively). Two main approaches are taken in the literature - the superlative index number approach and production function estimation. Both make restrictive assumptions in order to obtain measures of productivity. The main advantage of the superlative index number approach, and the reason why we adopt it in our empirical specification, is that by exploiting assumptions about market behaviour we can allow a more flexible functional form for the production technology.

The key assumptions behind the superlative index number measures that we employ

⁹See Barro and Sala-i-Martin (1995) for further discussion of the empirical growth literatures on β and σ -convergence.

are a constant returns to scale translog production function and perfect competition.¹⁰ These imply that the share of a factor in total costs contains information on its marginal physical productivity, and therefore provides the correct weight for the factor input when measuring productivity. The translog production technology provides an arbitrarily close local approximation to any underlying constant returns to scale production technology.

We also report results using augmented superlative index number measures of TFP¹¹ that allow for some form of imperfect competition where price is a mark-up over marginal cost. More generally, we pay careful attention to measurement issues and we carry out a number of robustness checks designed to deal with measurement error (see section 4.2) that could in principle affect the estimated speed of technological catch-up λ .

The alternative approach of production estimation faces the challenge of estimating the parameters of the production function while also allowing for the endogeneity of factor input choices. Olley and Pakes (1996) and Levinsohn and Petrin (2003) develop methodologies to address this challenge under the assumption that the production technology is Cobb-Douglas.¹² Although we also use the Olley-Pakes methodology as a robustness test, we do not take this as our preferred measure of productivity, because we believe it is important in our application to allow for a more flexible production technology, and because the theoretical model underlying the Olley-Pakes methodology does not incorporate productivity catch-up across establishments, which is a central feature of our empirical framework.

We calculate the growth rate of TFP (ΔTFP_{it} , the empirical counterpart to $\Delta \ln A_{it}$) and the level of TFP in establishment i relative to the frontier in industry j ($TFPGAP_{it}$,

¹⁰See for example Caves et al. 1982a,b.

¹¹Following the ideas in Hall (1988), Roeger (1995) and Klette (1999).

¹²While other studies in the production function estimation literature consider translog functional forms following Christenson *et al.* (1973), these studies do not typically allow for the endogeneity of factor input choices.

the empirical counterpart to $\ln(A_j^F/A_i)_t$) using the following superlative index number:

$$\Delta TFP_{it} = \Delta \ln Y_{it} - \sum_{z=1}^Z \tilde{\alpha}_{it}^z \Delta \ln x_{it}^z, \quad (9)$$

where Y denotes output, x^z is use of factor of production z , $\tilde{\alpha}_t^z$ is the Divisia share of output ($\tilde{\alpha}_{it}^z = (\alpha_{it}^z + \alpha_{it-1}^z)/2$, where α_{it}^z is the share of the factor in output at time t), Z is the number of factors of production, and we impose constant returns to scale ($\sum_z \tilde{\alpha}_{it}^z = 1$). The factors of production included in Z are the value of intermediate inputs, the stock of physical capital, and the numbers of skilled and unskilled workers. This formulation assumes that production technology is homogeneous of degree one and exhibits diminishing marginal returns to the employment of each factor alone. We allow factor shares to vary across establishments and time, which is consistent with the large degree of heterogeneity in technology observed even within narrowly defined industries.¹³

To allow for potential measurement error in the shares of factors of production in output, α_{it}^z , we exploit the properties of the translog production function following Harrigan (1997). Under the assumption of a translog production technology and constant returns to scale, α_{it}^z can be expressed as the following function of relative factor input use:

$$\alpha_{it}^z = \xi_i + \sum_{z=2}^Z \phi_j^z \ln \left(\frac{x_{it}^z}{x_{it}^1} \right), \quad (10)$$

where ξ_i is an establishment-specific constant and where, when imposing constant returns to scale, we have normalized relative to factor of production 1. If actual factor shares deviate from their true values by an i.i.d. measurement error term, then the parameters of this equation can be estimated by fixed effects panel data estimation, where we allow the coefficients on relative factor input use to vary across 4-digit industries j . The fitted values from this equation are used as the factor shares in our calculation of (9) and below.

However, this correction in fact has little impact on our results.

¹³We assume here for simplicity that technological change is Hicks neutral, in the sense of raising the marginal productivity of all factors proportionately.

The level of TFP is measured using an analogous superlative index number, where TFP in each establishment is evaluated relative to a common reference point - the geometric mean of all other establishments in the same industry (averaged over all years). The measure of relative TFP is,

$$MTFP_{it} = \ln \left(\frac{Y_{it}}{\bar{Y}_j} \right) - \sum_{z=1}^Z \sigma_i^z \ln \left(\frac{x_{it}^z}{\bar{x}_j^z} \right), \quad (11)$$

where a bar above a variable denotes a geometric mean; that is, \bar{Y}_j and \bar{x}_j^z , are the geometric means of output and use of factor of production z in industry j . The variable $\sigma_i^z = (\alpha_i^z + \bar{\alpha}_j^z)/2$ is the average of the factor share in establishment i and the geometric mean factor share. We again allow for measurement error using the properties of the translog production technology (see equation (10) above), and we impose constant returns to scale so that $\sum_z \sigma_i^z = 1$.

Denote the frontier level of TFP relative to the geometric mean $MTFP_{jt}^F$. Subtracting $MTFP_{it}$ from $MTFP_{jt}^F$, we obtain a superlative index of the productivity gap between an establishment and the frontier in an industry-year. This is denoted by $TFPGAP_{it}$ and is the empirical counterpart to $\ln \left(A_j^F / A_i \right)_t$,¹⁴

$$TFPGAP_{it} = MTFP_{jt}^F - MTFP_{it}. \quad (12)$$

3.2 Data

Our empirical analysis uses a rich and comprehensive micro panel data set. Our main source of data is the Annual Respondents Database (ARD). This is collected by the UK Office for National Statistics (ONS) and it is a legal obligation for firms to reply. These data provide us with information on inputs and output for production plants located in the UK.¹⁵ We

¹⁴Note that equation (11) may be used to obtain a bilateral measure of relative TFP in any two establishments a and b . Since we begin by measuring TFP compared to a common reference point (the geometric mean of all establishments), these bilateral measures of relative TFP are transitive.

¹⁵Basic information (employment, ownership structure) is available on all plants located in the UK. Detailed data on inputs and outputs is available on all production establishments with more than 100 employees and for a stratified sample of smaller establishments. The cut off point over which the population of establishments is sampled increases from 100 in later years. All of our results use the inverse of the sampling

use data at the establishment level.¹⁶ The country of residence of the ultimate owner of the establishment is also contained in the data. This is collected every year by the ONS from the Dun and Bradstreet publication Who Owns Whom. Output, investment, employment and wages by occupation, and intermediate inputs are reported in nominal terms for each establishment. We use data for all of Great Britain from 1980 to 2000 for 189 4-digit manufacturing sectors. In the calculation of TFP we use information on gross output, capital expenditure, intermediate inputs, and on the number of skilled (Administrative, Technical and Clerical workers) and unskilled (Operatives) workers employed and their respective wagebills.

We use price deflators for output and intermediate goods at the 4-digit industry level produced by the ONS. Price indices for investment in plant and machinery are available at the 2-digit level and for investment in buildings, land and vehicles at the aggregate level. Capital stock data is constructed using the perpetual inventory method with the initial value of the capital stock estimated using industry level data.

The ARD contains more detailed information on both output and inputs than is typically available in many productivity studies, and our analysis is undertaken at a very disaggregated level. This enables us to control for a number of sources of measurement error and aggregation bias suggested in the literature on productivity measurement. In addition, because response to the survey is compulsory, there is effectively no bias from non-random responses. We use a cleaned up sample of establishments that conditions on establishments being sampled for at least 5 years.¹⁷ We include a sample selection correction

probability as weights to correct for this. For further discussion of the ARD see Griffith (1999) and Barnes and Martin (2002).

¹⁶Establishments correspond to ‘lines of business’ of firms, the level at which production decisions are likely to be made. An establishment can be a single plant or a group of plants operating in the same four-digit industry; the number of plants accounted for by each establishment is reported. Establishments can be linked through common ownership.

¹⁷We drop very small 4-digit industries (with less than 30 establishments) in order to implement our procedure for smoothing factor shares (described in the next section), and drop small establishments (with less than 20 employees). We also apply some standard data cleaning procedures. We drop plants with negative value added, and condition on the sum of the shares of intermediate inputs, skilled and unskilled

term in the econometric analysis that controls for non-random survival of establishments. Measurement error is likely to be larger in smaller establishments, and therefore we also weight observations by employment.

3.3 Productivity growth and dispersion

In our data we see substantial variation in rates of productivity growth and convergence across establishments and industries. Table 1 provides summary statistics on our main measures. Growth in TFP in establishments in our estimation sample averaged 0.3% per annum over the period 1980 to 2000.¹⁸ For this set of establishments, many report negative average TFP growth rates during the period. This is largely driven by the recessions in the early 1980s and 1990s, and is consistent with the findings of industry-level studies for the UK and other countries.¹⁹ Over this same period labour productivity growth in our sample averaged 3.4% per annum across all industries. In our econometric specification, we explicitly control for the effects of the two recessions over this period and macroeconomic shocks on TFP growth by including a full set of time dummies. The standard deviation in TFP growth across the whole sample is 0.129, which shows that there is substantial variation in growth rates.

Figures 1 and 2 show the distribution of relative TFP (MTFP, as defined by (11)) for two example 2-digit industries. Each year we plot the distribution between the 5th and 95th percentile, with the line in the middle of each grey bar being the median. All industries display persistent productivity dispersion. This is explained in our empirical framework by variation in establishment innovative capabilities, and the fact that it takes time to catch-up with a constantly advancing frontier. The industry in Figure 1, office machinery and

workers in output being between 0 and 1.

¹⁸Disney et al (2003) report annual TFP growth of 1.06% between 1980 and 1992. In our sample annual TFP growth averaged 1% over the 1980s.

¹⁹Cameron, Proudman, and Redding (1998) report negative estimated rates of TFP growth for some UK industries during 1970-92, while Griliches and Lichtenberg (1984) report negative rates of TFP growth for some US industries during an earlier period.

computer equipment, shows stronger growth and less dispersion of productivity around the geometric mean than the industry in Figure 2, footwear and clothing. Over time, as industries converge towards steady-state, our empirical framework implies that productivity dispersion may rise or fall, depending on the relationship between the initial distribution of productivity across establishments and the steady-state distribution. Figure 3 summarizes changes in productivity dispersion for all 4-digit industries in our sample, by plotting changes in the sample standard deviation of relative TFP using a histogram. In 107 industries the standard deviation of relative TFP declined, while in 82 industries it increased, over the period 1980-2000.

Table 2 shows the proportion of establishments that transit between quintiles of their 4-digit industry TFP distribution. The rows show the quintile at time $t - 5$, while the columns show the quintile at time t . For example, the row marked quintile 5 shows that, of the establishments that were in the bottom quintile of their industry's TFP distribution, five years later 22% of those that survive have moved up to the top quintile, 24% have moved to the second quintile, 20% to the third, 21% to the fourth, and 13% remain in the bottom quintile. This transition matrix shows that persistent cross-section dispersion is accompanied by individual establishments changing their position within the productivity distribution, as implied by the framework discussed above.

These descriptive statistics show that there is substantial variation in growth rates, even within industries. And these differences in growth rates translate, in some cases, into persistently different level of TFP. Our framework developed above provides one explanation for this, and below we look at how well it describes the variation we see in the data.

3.4 The productivity frontier

Before turning to the econometric evidence it is worth considering what we are capturing in our measure of the distance to the frontier. We begin by using the establishment with the

highest level of TFP to define the frontier. This approach has the advantages of simplicity and of closely following the structure of the empirical framework. Another attraction is that it potentially allows for endogenous changes in the frontier, as one establishment first catches up and then overtakes the establishment with the highest initial level of TFP.

For our econometric estimates it is not important whether we correctly identify the precise establishment with the highest level of true TFP or, more generally, whether we correctly measure the exact position of the productivity frontier. The TFP gap between establishment i and the establishment with the highest TFP level is being used as a measure of the *potential* for productivity catch-up. What matters for estimating the parameters of interest is the correlation between our measure and true unobserved distance from the productivity frontier.

Year on year fluctuations in measured TFP may be due partly to measurement error and this could lead to mis-measurement in the location of the frontier. The rich source of information that we have on establishments in the ARD, and the series of adjustments that we make in measuring TFP, allow us to control for many of the sources of measurement error suggested in the existing literature. Nonetheless, it is likely that measurement error remains and we consider a number of robustness tests. To abstract from high frequency fluctuations in TFP due to measurement error, we define the productivity frontier as an average of the five establishments with the highest levels of TFP relative to the geometric mean. As another robustness test, we replace our measure of distance to the frontier by a series of dummies for the decile of the industry productivity distribution where an establishment lies. While it may be hard to accurately measure an establishment's exact level of productivity, the decile of the productivity distribution where an establishment lies is likely to be measured with less error. We also address measurement error in TFP using instrumental variables estimation and by estimating the alternative ADL(1,1) representation of our econometric equation as discussed further below.

Table 1 provides descriptive statistics and shows that, on average, the log TFP gap is 0.548, which implies that on average the frontier establishment has TFP 73% higher than non-frontier establishments ($\exp(0.548) = 1.73$). The table also shows that there is substantial variation in the size of the TFP gap, which we exploit below in estimating the contribution of productivity catch-up to productivity growth.

4 Empirical results

We start by presenting estimates of the correlation between TFP growth and an establishment's distance behind the frontier. We then consider robustness and present additional evidence that our interpretation better explains variation in the data than alternative hypotheses such as measurement error. We then use our estimates to quantify the importance of productivity catch-up in the growth process, under the assumption that our interpretation of the estimates is the correct one. Finally, we investigate the implied contribution of US-owned affiliates to productivity catch-up.

4.1 Productivity dynamics

We start by examining the correlation between an establishment's TFP growth rate and distance to the TFP frontier in their 4-digit industry, controlling for only year effects and industry fixed effects. This is shown in the first column of Table 3. We see that there is a positive and significant correlation. This is our basic specification in equation (2). In column 2, we add age, an indicator for whether the establishment is an affiliate of a US multinational or an affiliate of another foreign multinational, and a term to correct for possible bias due to sample selection, (the selection equation used to derive the inverse mills ratio is shown in table A1 in the Appendix). The coefficient on age never enters significantly, while the dummy for US-owned establishments enters with a positive and significant coefficient, indicating that the UK-based affiliates of US multinationals experience around a half of one

percent faster growth than the average UK establishment. This is consistent with the idea that the affiliates of US multinationals have higher levels of innovative capabilities (γ_i) in equations (2) and (8). We also include a dummy indicating whether an establishment is an affiliate of a multinational from any other foreign country and find that this is statistically insignificant, implying that it is only the affiliates of US multinationals that exhibit the statistically significant difference in innovative capabilities. This pattern of coefficients is in line with the findings in other empirical work for the UK.²⁰ As expected, the coefficient on the inverse Mills ratio is positive and significant, indicating that firms that survive have, on average, higher growth rates. In line with this, when we look at exiting firms we see that they are mainly exiting from the lower deciles of the TFP growth distribution.

In the third column we add establishment-specific effects. These allow innovative capabilities (γ_i) in equation (2) to vary across establishments, and control for unobservable characteristics that may be correlated with the TFP gap. We find a positive and significant effect of the TFP gap term - other things equal, establishments further behind the frontier in their 4-digit industry have faster rates of productivity growth than firms closer to the frontier. This is consistent with the idea that there is productivity catch-up. The magnitude of the coefficient increases slightly when we include establishment fixed effects. This makes sense, omitted establishment characteristics that raise the level of productivity (e.g. good management that promotes higher innovative capabilities γ_i) will be negatively correlated with the productivity gap term (from equation (8) these establishments are more likely to be nearer to the technology frontier than other establishments) and so lead to negative bias in the coefficient on the technology gap. Including establishment fixed effects means that our econometric equation focuses on variation in the time-series relationship between productivity in individual establishments and productivity in the frontier.

²⁰Criscuolo and Martin (2005) provide evidence for the UK showing that the UK affiliates of US multinationals have a productivity advantage over UK and other foreign multinationals (located in the UK).

In the fourth column we add in the growth rate of TFP in the frontier, as in the ECM representation (equation 5). This specification allows for a more flexible long-run relationship between frontier and non-frontier TFP. The frontier growth rate enters with a positive and significant coefficient - establishments in industries where the frontier is growing faster also experience faster growth. The coefficient on the gap term remains positive and significant. This pattern of estimates is consistent with the positive cointegrating relationship between frontier and non-frontier TFP implied by our empirical model of productivity catch-up ($\alpha_2 > 0$, $(1 - \alpha_1) > 0$ and $\alpha_3 = (1 - \alpha_1) - \alpha_2 > 0$ in equation (4)).

We now consider a number of potential concerns about the robustness of these results and alternative explanations for our findings, before turning to a discussion of the role of foreign multinationals. We consider three main issues - measurement error and endogeneity, parameter heterogeneity, and mean reversion.

4.2 Measurement error

As mentioned above, a major concern is that TFP_{it-1} appears on both the right and left hand sides of our regression specification (2). Therefore, any measurement error in TFP_{it-1} would induce a spurious correlation between TFP growth and distance to the frontier. We address this concern in a number of ways. First, we control for many sources of measurement error in our TFP indices by using detailed micro data (as described above). Second, rather than using the continuous measure of distance to the frontier we use a discrete version indicating which decile, in terms of distance to the frontier, the establishment is in. Using deciles, rather than the actual distance to frontier, means that TFP_{it-1} does not enter directly on the right-hand side. Indeed, while it may be hard to accurately measure an establishment's exact level of productivity, the decile of the productivity distribution to which the establishment belongs is likely to be measured with less error. Although the decile dummies reduce the extent of variation in productivity relative to the frontier, this

works against us by making it harder to identify the relationship of interest. The estimates with decile dummies are shown in column 5 of Table 3. We find that, conditional on the other covariates, establishments in the tenth decile (those furthest away from the frontier) experience 25% faster TFP growth than those very close to the frontier. The coefficients on the decile dummies are monotonically declining, with those nearest the frontier experiencing the slowest growth rates.²¹

We also take three further approaches. First, in column 1 of Table 4 we include an alternative measure of distance from the frontier, based on the average TFP in the five establishments with the highest measured TFP levels.²² If measurement error is imperfectly correlated across establishments, averaging will reduce the relative importance of measurement error so that the average TFP of the top five establishments provides a closer approximation to the true productivity frontier. Again we find a positive and significant coefficient on the TFP gap. In column 2 of Table 4 we instrument relative TFP using lagged values of the TFP gap term. We use the t-2 and t-3 lags, both of which are statistically significant with an R-squared in the reduced form regression of 0.50, indicating that the instruments have some power. The instruments address the concern that contemporaneous measurement error in TFP_{it-1} will induce a spurious correlation between ΔTFP_{it} on the left-hand side of equation (2) and $TFPGAP_{it-1}$ on the right-hand side of the equation. In the IV specification, we focus solely on variation in $TFPGAP_{it-1}$ that is correlated with the productivity gap at time t-2 and t-3. Again, we find a similar pattern of results. The coefficient on the gap term increases substantially (as does the standard error). This is due to the instrumenting rather than the change in sample induced by the use of information on longer lags.

²¹We also experimented with quartile dummies, since measuring the quartile of the productivity distribution to which the establishment belongs is likely to be measured with even less error. Again we found a similar pattern of results, with establishments in lower quartiles experiencing statistically significantly higher rates of productivity growth.

²²This leads to a smaller sample size because we omit the frontier establishments from our estimating sample, so in this case we are omitting the five top establishments in each industry-year.

Second, another concern about measurement error is that TFP is measured under the assumption of perfect competition, as discussed above. In column 3 of Table 4 we adjust the factor shares by an estimate of the markup (calculated at the 2-digit industry-year level). The coefficient on the gap term remains positive and significant.

Third, in column 4 of Table 4 we use an alternative measure of TFP. We implement the Olley-Pakes technique to estimate the level of TFP and from this calculate the growth rates and the gap. Again we find a similar pattern of results, with the coefficient on the gap positive and significant.

4.3 Parameter heterogeneity

Our baseline estimation results pool across industries, imposing common slope coefficients, and a possible concern is that there might be parameter heterogeneity across industries - for example, in some industries knowledge may spillover more easily than in others. To allow for this we re-estimated the model separately for each 2-digit industry.²³ As shown in column 6 of Table 3, this yielded a similar pattern of results. The median estimated coefficients, across 2-digit industries, were 0.134 for distance from the productivity frontier, 0.0006 for age, 0.013 for the US dummy and -0.01 for the other foreign dummy. The coefficient on distance to the frontier was positive in all cases, and in 15 out of 17 2-digit industries it was significant at the 5% level. These estimates lie close to the baseline within groups estimates reported in column 3 of Table 3.²⁴

²³See, for example, the discussion in Pesaran and Smith (1995).

²⁴One concern we might have is that there are industry specific shocks that are correlated with distance to the frontier, yet we only allow for common time shocks. The results in column 6 of Table 3 where we have estimated separately for each 2-digit industry allows for separate time effects across 2-digit industries. In addition, we ran the specification with deciles (column 5 of Table 3) including 4-digit industry time dummies and the coefficients on the decile dummies remain similar, for example, the coefficient (standard error) on decile 2 is 0.065 (0.006) and on decile 10 is 0.261 (0.017).

4.4 Mean reversion

A further concern with our results is whether we are picking up productivity catch-up or mean reversion. The statistical significance of the establishment fixed effects provides evidence against reversion to a common mean value for productivity across all establishments. There remains the concern that each establishment may be reverting to its own mean level of productivity. A negative realization of the stochastic shocks to technology last period, u_{it-1} , leads to a lower value of lagged productivity, A_{it-1} , and a larger value of distance from the frontier, A_{Fjt-1} . Reversion to the establishment's mean level of productivity would result in a faster rate of TFP growth, inducing a positive correlation between establishment productivity growth and lagged distance from the frontier. Under this interpretation, the identification of the parameters of interest is driven solely by variation in A_{it-1} . In contrast, according to our productivity catch-up hypothesis, variation in the position of the frontier, A_{Fjt-1} , also plays an important role.

In a first robustness test, we directly examine the importance of the position of the frontier by estimating the ADL(1,1) representation of our econometric equation in (4). In this specification, the terms for lagged own establishment productivity, contemporaneous frontier productivity and lagged frontier productivity enter separately in the equation, allowing us to directly test their statistical significance. In column 1 of Table 5, we find that the terms for contemporaneous and frontier TFP are individually and jointly statistically significant, providing direct evidence that variation in the position of the frontier plays an important role in determining establishment productivity growth in addition to the establishment's own lagged productivity.

In a second robustness test, we consider the alternative hypothesis that each establishment reverts to its own mean level of TFP. We exploit the decile dummies used above. Under the alternative hypothesis, establishment TFP follows an AR(1) process with reversion to

an establishment specific mean:

$$\Delta \ln A_{it} = \gamma_i + \lambda \ln A_{it-1} + u_{it}, \quad |\lambda| < 1. \quad (13)$$

Under the null hypothesis that productivity catch-up plays an important role in determining establishment productivity growth, as in equation (2), the location of the frontier should also be important. We test this prediction by including the decile dummies in equation (13) and testing the joint statistical significance of the coefficients on the decile dummies. In column 2 of Table 5, we find that the coefficients on the decile dummies are highly statistically significant. The coefficients on the decile dummies have the expected sign, and the coefficients for the lower deciles are typically larger than those for the higher deciles as predicted by our empirical model of productivity catch-up. As an additional robustness check, we repeat this specification allowing for a more general autoregressive process for establishment productivity than AR(1) by including an additional lag in the level of establishment own productivity in column 3. Again we find a very similar pattern of results.

To further address the concern that contemporaneous measurement error in establishment own productivity at t-1 may induce a spurious correlation between left and right-hand side variables, column 4 returns to the AR(1) specification from column 2, but instruments the lagged level of establishment own productivity with its value at t-2 and t-3. We continue to find correctly signed and statistically significant coefficients on the decile dummies, as implied by our empirical model of productivity catch-up.²⁵ Taken together, these results provide support for the idea that the location of the productivity frontier influences establishment productivity growth in addition to the establishment's own level of productivity.

²⁵We also experimented with specifications using dummies for the quintiles or quartiles of the productivity distribution where an establishment lies, which are likely to be measured with less error than the decile of the distribution. We continued to find a similar pattern of results.

4.5 Economic importance

Our results are subject to a number of caveats. While our findings are consistent with productivity catch-up, we cannot directly observe technology transfer and we cannot definitively separate the contribution of true productivity catch-up from the potential biases introduced by measurement error and mean reversion. With these caveats in mind, and as an additional check on the reasonableness of the results, we now examine the implied magnitude of the contribution of productivity catch-up to productivity growth in non-frontier establishments.

If we take the coefficient on the productivity gap, multiply this by the gap for each individual establishment, and represent this as a percentage of the establishment's own annual growth rate, our results imply that for the median establishment productivity catch-up accounts for 9% of annual growth, (taking the mean across establishments, rather than the median we find that productivity catch-up accounts for on average 8% of annual productivity growth). If we instead express the contribution of productivity catch-up as a percentage of predicted growth (omitting the idiosyncratic element) our results imply that for the median establishment it accounts for 26% of growth (taking the mean across establishments, productivity catch-up accounts for 98% of annual predicted productivity growth).²⁶

As discussed above, if the affiliates of US multinationals have higher innovative capabilities (γ_i), they will frequently lie at the productivity frontier within industries (equation (8)). In the next section, we use our estimates to back out the implied contribution of US affiliates to non-frontier productivity growth, again under the assumption that our estimates are capturing true productivity catch-up towards the frontier.

²⁶If we simply take the coefficient on the gap and multiply it by the average gap, we obtain a much larger estimate of the contribution of technology transfer. This is driven by the influence of outlying observations that affect mean productivity growth and levels.

4.6 Foreign ownership and productivity dynamics

In many ways, foreign-owned establishments are just like any other. However, a large theoretical and empirical literature finds that they are on average more productive than domestic-owned establishments, and they may have access to superior technology from the source country where the parent firm is based.²⁷ In the UK, the majority of foreign investment has come from the US, and many papers have documented the fact that the US is the technological leader in a large number of industries. In addition, Criscuolo and Martin (2005) show that it is specifically US multinationals operating within the UK that have a productivity advantage over UK and other foreign-owned multinationals. The positive and sometimes significant dummy on US-owned establishments in Tables 3, 4 and 5 suggests that this is also the case in our sample. We also include a dummy to control for foreign affiliates of all other nationalities, but this is never significant. Therefore, in this section we focus our attention on the implied contribution of US multinationals to the productivity growth of non-frontier establishments.

Column 1 of Table 6 shows that, using data on the population of plants, US affiliates account for around 9% of employment, ranging from 30% in the high-tech office machinery and computer equipment sector, to zero in the leather and leather goods sector. Column 2 shows that US affiliates were the frontier establishment around 13% of the time across industries over the period 1980-2000. There is again a large range, from US affiliates being at the frontier around a quarter of the time in non-metallic mineral products to only three percent of the time in textiles. As we would expect, the likelihood that US affiliates are at the technological frontier is positively correlated with their presence in an industry. US-owned establishments have the highest presence in high-tech industries such as office

²⁷For empirical evidence on the higher productivity of foreign-owned establishments and multinationals more generally, see Criscuolo and Martin (2005), Doms and Jensen (1998), Griffith (1999) and Griffith and Simpson (2004). This evidence is consistent with there being fixed costs to becoming a multinational firm, as formalized in Helpman *et al.* (2004) and Markusen (2002).

machinery and computer equipment, chemicals and instrument engineering, and make up the technological frontier over 20% of the time in the latter two sectors.

The third column examines the difference in productivity between frontier US-owned establishments and the next most productive non-US-owned establishment. When the frontier is a non-US-owned establishment this figure is zero. This distance averages two percent across all manufacturing industries, and ranges from zero to 5 percent. Looking just at cases where a US affiliate is the frontier, on average productivity in the US affiliate is 19% greater than productivity in the next most productive non-US-owned establishment. To back out the implied contribution of US establishments to productivity catch-up for non-frontier UK-based establishments, we calculate the proportion of productivity catch-up (λTFP_{it-1}) due to US affiliates ($\lambda (TFP_{it-1} - TFP_{it-1}^{*nf})$), where TFP_{it-1}^{*nf} is a measure of the productivity gap based on the next most productive non-US owned establishment:

$$\frac{\lambda (TFP_{it-1} - TFP_{it-1}^{*nf})}{\lambda TFP_{it-1}} = 1 - \frac{TFP_{it-1}^{*nf}}{TFP_{it-1}}.$$

We calculate this measure for each individual establishment and take the mean over all establishments. This is shown in column 4 of Table 6. We see that the implied contribution to productivity catch-up ranges from zero, in industries where no US affiliates are present at the frontier, to 20% in mechanical engineering, and averages 10%. The pattern across industries suggests that US affiliates may make a larger contribution to productivity catch-up in high-technology industries such as mechanical engineering, instruments, office machinery and data processing equipment and chemicals.

Finally we experimented with modifying our main specification in column 3 in Table 3 to include an additional interaction term between TFP_{it-1} and a dummy variable indicating that the frontier establishment in the previous period was US-owned, to see if, for a given level of technological leadership, there was any difference in the extent of productivity catch-up when a US-owned establishment was at the technological frontier.

We found that, for a given technological gap, catch-up did not vary with the ownership status of the frontier establishment, consistent with the idea that any high productivity firm can act as a conduit for productivity catch-up, not only foreign-owned multinationals.

5 Conclusions

The recent literature has emphasized deregulation and the opening up of markets as a key source of productivity growth. One important mechanism through which this works is through productivity catch-up or technology transfer from high productivity domestic firms, and technology sourcing and inward investment from more technologically advanced economies. But the importance of productivity convergence raises the puzzle of how it can be reconciled with persistent dispersion in productivity levels across establishments within narrowly defined industries.

In this paper we used micro panel data to investigate the correlation between an establishment's TFP growth and its distance from the technological frontier. We did this in a way that also allowed for persistent dispersion as an equilibrium outcome. We found statistically significant and quantitatively important evidence that is consistent with productivity catch-up to the technological frontier. While not necessarily definitive, our findings on the importance of productivity catch-up suggest there may be a richer process for the dynamics of establishment productivity than implied by many existing models of industry equilibrium where establishment productivities follow independent stochastic processes.

Fixed costs of becoming a multinational and US technological leadership in a range of industries imply that the affiliates of US multinationals are likely to be more productive than many purely domestic firms. Consistent with this idea, we find that US-owned establishments are frequently the most productive establishments within industries. We use our econometric specification to quantify their implied contribution towards productivity growth in non-frontier establishments. This contribution is larger in high-technology indus-

tries, such as mechanical engineering, instruments and office machinery and data processing equipment, where the US frequently exerts technological leadership.

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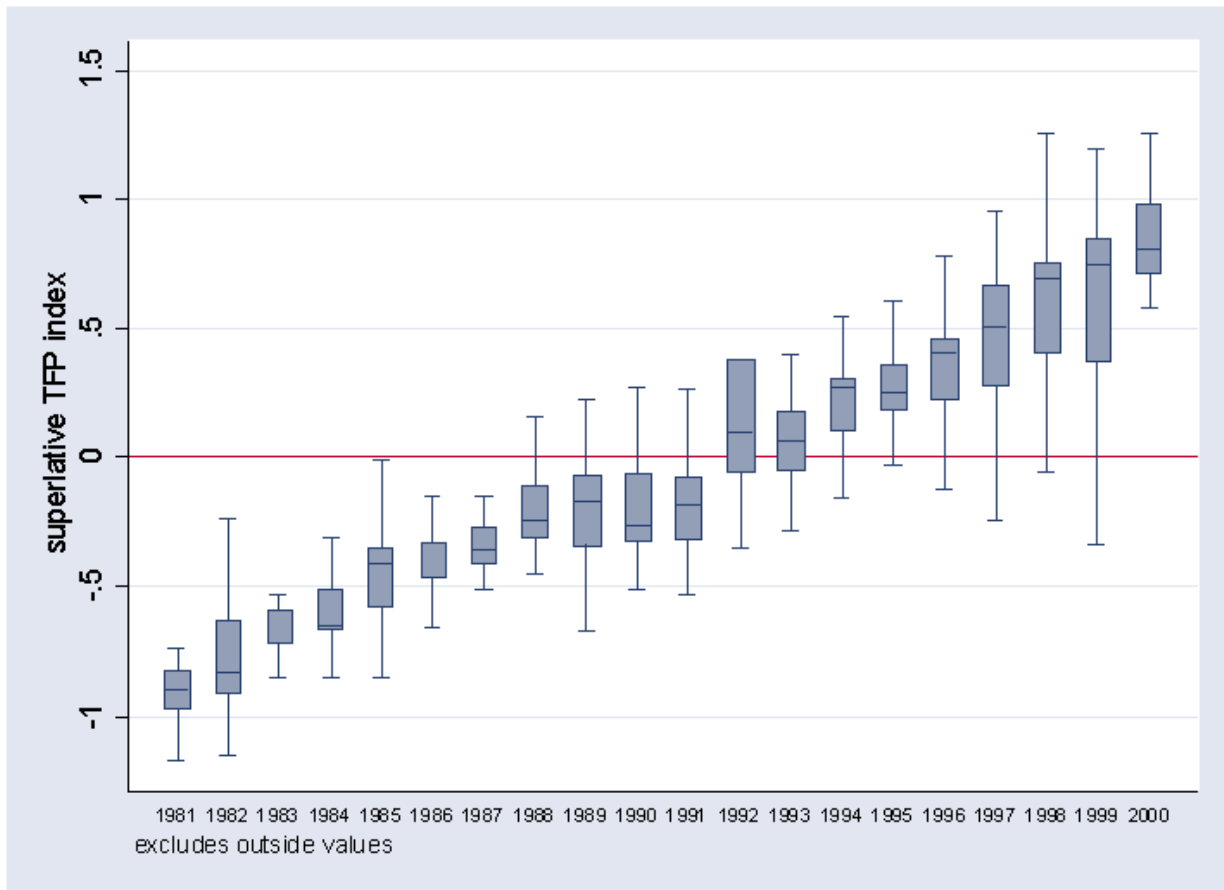
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Table 1: Descriptive statistics

Variable	Mean	Standard deviation
ΔTFP_{ijt}	0.003	0.129
$TFPGAP_{ijt-1}$	0.548	0.317
ΔTFP_{Fjt}	0.003	0.303
Age	8.127	5.122
US dummy	0.120	0.325
Other foreign dummy	0.105	0.306

Note: The sample includes 103,664 observations on all non-frontier establishments over the period 1980-2000. Means are weighted by the inverse of the sampling probability and employment.

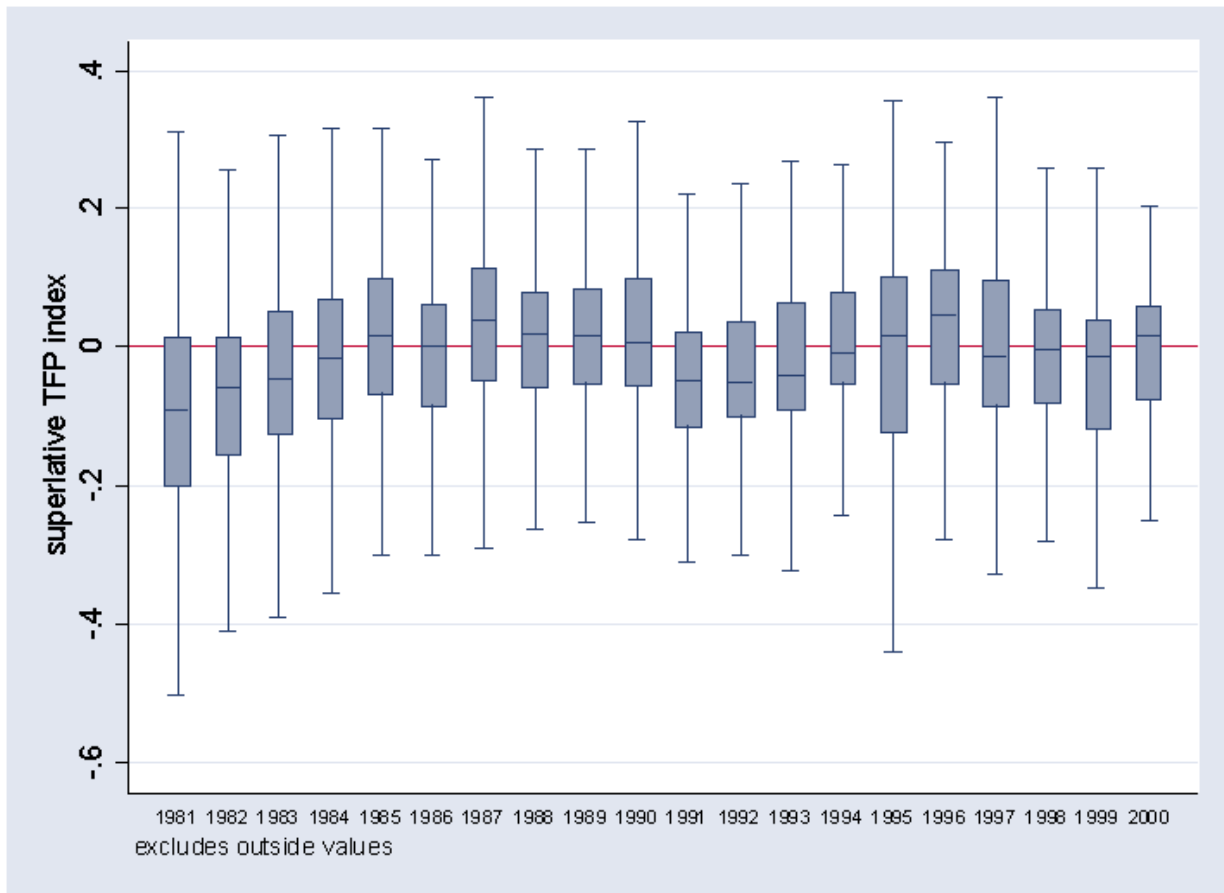
Source: authors' calculations using the ARD (Source: ONS).

Figure 1: Evolution of TFP in the office machinery and computer equipment industry

Note: The figure shows the distribution of TFP in 2-digit industry no.33 over time. TFP in each establishment is measured relative to the geometric mean of all other establishments in the same 4-digit industry (averaged over all years). The sample includes 627 observations on non-frontier establishments over the period 1981-2000. The horizontal bar shows the median, the top and bottom of the horizontal lines represent the 95th and 5th percentile respectively.

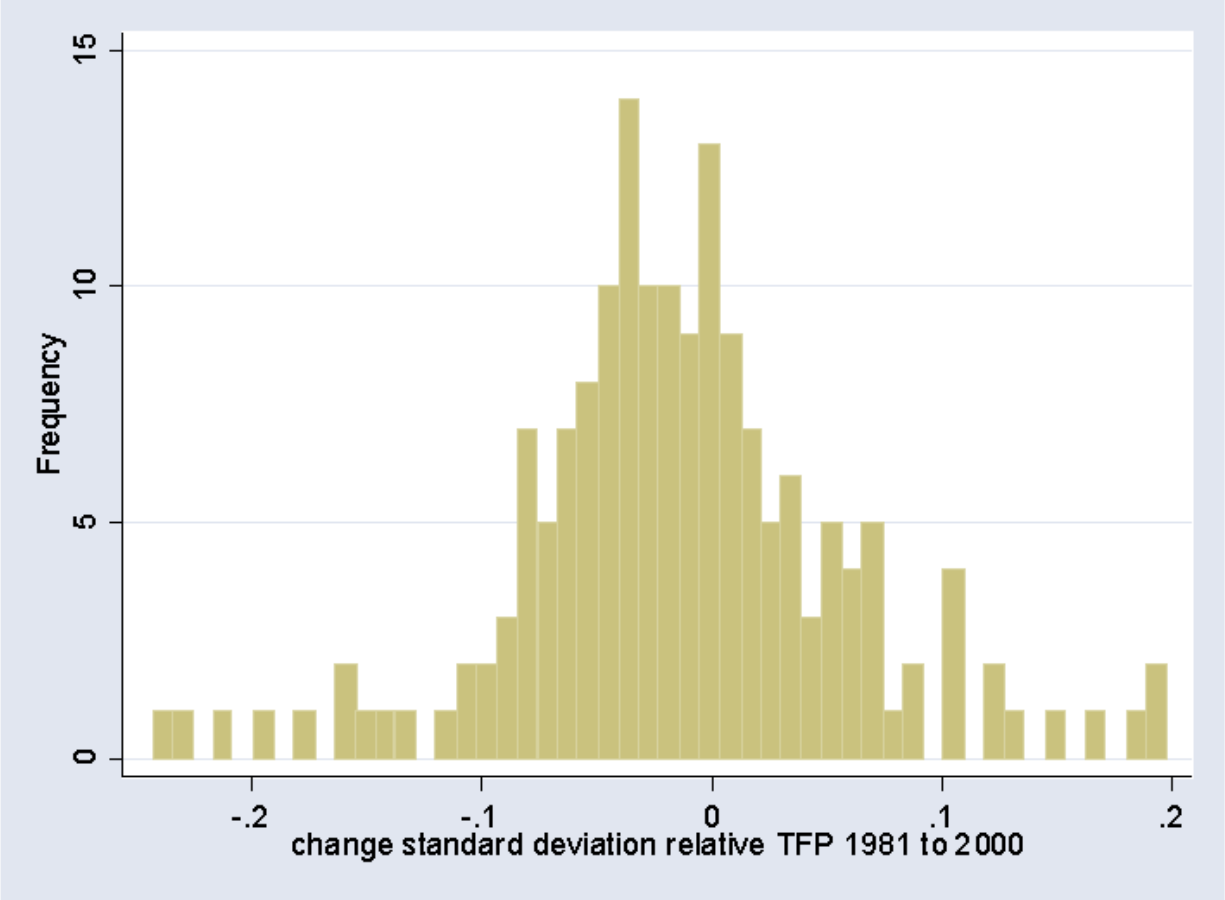
Source: authors' calculations using the ARD (Source: ONS).

Figure 2: Evolution of TFP in the footwear and clothing industry



Note: The figure shows the distribution of TFP in 2-digit industry 45 over time. TFP in each establishment is measured relative to the geometric mean of all other establishments in the same 4-digit industry (averaged over all years). The sample includes 6129 observations on non-frontier establishments over the period 1981-2000. The horizontal bar shows the median, the top and bottom of the horizontal lines represent the 95th and 5th percentile respectively. Source: authors' calculations using the ARD (Source: ONS).

Figure 3: Change in standard deviation of TFP within 4-digit industries, 1981-2000



Note: The figure shows the distribution of the change in the standard deviation over the period 1981-2000 for the 189 4-digit industries in our sample.
Source: authors' calculations using the ARD (Source: ONS).

Table 2: Transition matrix

Quintile of TFP distribution, t-5	Quintile of TFP distribution t					Total
	1	2	3	4	5	
1	37.71	29.39	18.27	9.41	5.22	100
2	26.46	28.06	25.16	13.76	6.57	100
3	17.39	26.48	25.13	22.08	8.92	100
4	18.03	20.22	28.58	21.92	11.25	100
5	22.19	23.81	19.81	21.47	12.73	100
Total	24.75	25.88	23.36	17.35	8.67	100

Note: The table shows the proportion of establishments by quintile of the TFP distribution within their 4-digit industry in period t-5 and t, averaged over the four five year periods in our sample. The quintiles are defined across all establishments in our sample (including entrants and exitors), while only establishments that are present in both period t-5 and t are included in the table. The figures are weighted by the inverse of the sampling probability and employment. Source: authors' calculations using the ARD (Source: ONS).

Table 3: Catch-up model

Dep var: ΔTFP_{ijt}	(1)	(2)	(3)	(4)	(5)	(6)
Obs	103,664	103,664	103,664	103,664	103,664	103,664
ΔTFP_{Fjt}				0.111 (0.012)		
$TFPGAP_{ijt-1}$	0.091 (0.012)	0.091 (0.012)	0.117 (0.015)	0.199 (0.022)		0.134
Age		0.0002 (0.0005)	0.0003 (0.0006)	0.0002 (0.0006)	0.001 (0.0004)	0.0006
US dummy		0.005 (0.002)	0.007 (0.005)	0.010 (0.005)	0.007 (0.006)	0.013
Other foreign		-0.009 (0.006)	-0.020 (0.014)	-0.020 (0.014)	-0.022 (0.015)	-0.010
DD2					0.062 (0.006)	
DD3					0.098 (0.008)	
DD4					0.123 (0.008)	
DD5					0.146 (0.010)	
DD6					0.164 (0.009)	
DD7					0.188 (0.011)	
DD8					0.224 (0.013)	
DD9					0.251 (0.013)	
DD10					0.254 (0.017)	
Inverse mills ratio		0.006 (0.004)	0.043 (0.010)	0.038 (0.011)	0.021 (0.012)	0.032
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
4-digit industry dummies	Yes	Yes	-	-	-	-
Within groups	No	No	Yes	Yes	Yes	Yes
R ²	0.073	0.074	0.152	0.194	0.250	

Note: Regressions are estimated on all non-frontier establishments for 1980-2000. All columns are weighted by the inverse of the sampling probability and employment. Standard errors in brackets are clustered at the 4-digit industry.

ΔTFP_{Fjt} is tfp growth in the frontier. $TFPGAP_{ijt-1}$ is tfp relative to frontier in the previous period. DD* are dummies representing the decile of the within 4-digit industry year distribution of $TFPGAP_{ijt-1}$ where DD10 is the decile for establishments with the largest gap with the frontier. DD1 the decile for those closest to the frontier is omitted. Column (6) reports the median of the coefficients from 2-digit industry level regressions.

Source: authors' calculations using the ARD (Source: ONS).

Table 4: Robustness

Dep var: ΔTFP_{ijt}	(1)	(2)	(3)	(4)
Obs	101,328	70,023	52,478	93,825
$TFPGAP_{ijt-1}$		0.400 (0.070)	0.138 (0.021)	0.054 (0.006)
$TFPGAP5_{ijt-1}$	0.327 (0.030)			
Age	0.001 (0.0006)	-0.0009 (0.0008)	0.0005 (0.001)	0.0009 (0.0005)
US dummy	0.004 (0.005)	0.012 (0.006)	-0.007 (0.009)	0.003 (0.005)
Other foreign	-0.021 (0.015)	-0.031 (0.019)	-0.022 (0.013)	-0.015 (0.012)
Inverse mills ratio	0.029 (0.011)	0.040 (0.021)	0.053 (0.018)	0.032 (0.010)
Control function in regression		-0.319 (0.070)		
Significance of instruments in reduced form		324.83		
F-statistics (P-value)		(0.000)		
R ² of reduced form		0.50		
Year dummies	Yes	Yes	Yes	Yes
Within groups	Yes	Yes	Yes	Yes
R ²	0.244	0.157	0.238	0.146

Note: Regressions are estimated on non-frontier establishments for 1980-2000. All columns are weighted by the inverse of the sampling probability and employment. Standard errors in brackets are clustered at the 4-digit industry. Column (1) uses a measure of distance to the frontier where the frontier is defined by the average level of TFP in the top five establishments. In column (2) the TFP gap term is instrumented using own lags dated t-2 and t-3. In column (3) the measure of TFP is adjusted for variation in markups at the 2-digit industry-year level. In column (4) we use Olley-Pakes/Pavnick estimates of TFP.

Source: authors' calculations using the ARD (Source: ONS).

Table 5: ADL(1,1) and ECM specifications

	(1)	(2)	(3)	(4)
Dependent variable	TFP_{ijt}	ΔTFP_{ijt}	ΔTFP_{ijt}	ΔTFP_{ijt}
Obs	103,664	103,664	84,232	70,023
TFP_{ijt-1}	0.545 (0.036)	-0.342 (0.051)	-0.375 (0.034)	-0.271 (0.035)
TFP_{ijt-2}			0.068 (0.016)	
$TFPF_{jt}$	0.044 (0.009)			
$TFPF_{jt-1}$	0.021 (0.008)			
Age	0.0012 (0.0005)	0.001 (0.0005)	0.0005 (0.0006)	-0.0004 (0.0008)
US dummy	0.006 (0.005)	0.006 (0.005)	0.010 (0.006)	0.010 (0.008)
Other foreign dummy	-0.019 (0.017)	-0.021 (0.016)	-0.024 (0.019)	-0.025 (0.020)
DD2		0.025 (0.005)	0.026 (0.007)	0.024 (0.007)
DD3		0.039 (0.009)	0.042 (0.009)	0.041 (0.009)
DD4		0.048 (0.010)	0.050 (0.010)	0.047 (0.010)
DD5		0.058 (0.010)	0.060 (0.010)	0.057 (0.010)
DD6		0.062 (0.013)	0.064 (0.011)	0.060 (0.010)
DD7		0.068 (0.015)	0.069 (0.013)	0.065 (0.013)
DD8		0.085 (0.017)	0.085 (0.014)	0.082 (0.013)
DD9		0.087 (0.021)	0.093 (0.016)	0.089 (0.017)
DD10		0.079 (0.023)	0.079 (0.019)	0.075 (0.020)
Inverse mils ratio	0.006 (0.015)	0.006 (0.014)	-0.006 (0.026)	-0.005 (0.030)
Control function in regression				-0.116 (0.032)
Significance of instruments in reduced form				10867.83
F-statistics (P-value)				(0.000)
R ² of reduced form				0.69
Year dummies	Yes	Yes	Yes	Yes
Within groups	Yes	Yes	Yes	Yes
R ²	0.678	0.307	0.310	0.318

Notes: Regressions are estimated on non-frontier establishments for 1980-2000. All columns are weighted by the inverse of the sampling probability and employment. Standard errors in brackets are clustered at the 4-digit industry. In column 1 frontier TFP ($TFPF_t$) and lagged frontier TFP ($TFPF_{t-1}$) are jointly significant. Dependent variable in columns 2 to 4 is TFP growth. In column 3 we add in TFP t-2 and in column 4 we instrument TFP t-1 with TFP t-2 and TFP t-3.

Source: authors' calculations using the ARD (Source: ONS).

Table 6: Implied contribution of affiliates of US multinationals, 1980-2000

Sector	US affiliates: Share of industry employment %	% of time frontier	Advancement of the frontier	Advancement of the frontier as a proportion of the total gap
22 metal manufacturing	5	17	0.02	0.07
24 non-metallic mineral products	4	24	0.04	0.15
25 + 26 chemicals and man-made fibres	18	23	0.05	0.14
31 metal goods n.e.s.	8	6	0.01	0.08
32 mechanical engineering	15	18	0.04	0.20
33 office machinery and data processing equipment	30	13	0.03	0.15
34 electrical and electronic engineering	10	10	0.01	0.06
35 motor vehicles and parts	16	17	0.05	0.10
36 other transport equipment	3	4	0.00	0.00
37 instrument engineering	20	22	0.02	0.13
41 + 42 food, drink and tobacco	6	14	0.02	0.06
43 textiles	4	3	0.01	0.02
44 leather and leather goods	0	0	0	0
45 footwear and clothing	2	4	0.01	0.03
47 paper, paper products and publishing	8	9	0.02	0.12
48 rubber and plastics	8	21	0.03	0.13
49 + 46 other manufacturing, timber	4	1	0.00	0.01
<i>All manufacturing</i>	<i>9</i>	<i>13</i>	<i>0.02</i>	<i>0.10</i>

Notes: All means are weighted by the inverse of the sampling probability and employment. Column (1) shows the annual average proportion of employment in each 4-digit industry with the 2-digit industry that is in affiliates of US firms, 1980-2000. Column (2) shows the percentage of times an affiliate of a US firm is the most productive establishment in its 4-digit industry. Column (3) shows how far the US affiliate advances the frontier (i.e. the distance between the US affiliate and the nearest non-US-owned establishment) when it is the frontier. This is the mean of $\ln(A_{F US} / A_{F Non-US})$. Column 4 shows the amount that affiliates of US firms advance the frontier (increase the TFP gap) divided by the total gap, calculated at the establishment level and averaged.

Source: authors' calculations using the ARD (Source: ONS).

Appendix

Table A1: First stage selection equation

Dependent variable = 1 if establishment survives (remains in sample)

Obs	166,576
Age	0.332 (0.003)
Age ²	-0.014 (0.00001)
Ln(real investment)	2.225 (0.402)
Ln(real investment) ²	0.016 (0.065)
Ln(real investment) ³	-0.017 (0.006)
Ln(real investment) ⁴	-0.00005 (0.00002)
Ln(real capital stock)	0.095 (0.509)
Ln(real capital stock) ²	-0.011 (0.102)
Ln(real capital stock) ³	0.003 (0.010)
Ln(real capital stock) ⁴	-0.00008 (0.0004)
Ln(real investment)* Ln(real capital stock)	-1.019 (0.184)
Ln(real investment)* Ln(real capital stock) ²	0.156 (0.028)
Ln(real investment)* Ln(real capital stock) ³	-0.008 (0.001)
Ln(real investment) ² * Ln(real capital stock)	0.021 (0.027)
Ln(real investment) ² * Ln(real capital stock) ²	-0.007 (0.004)
Ln(real investment) ² * Ln(real capital stock) ³	0.001 (0.0002)
Ln(real investment) ³ * Ln(real capital stock)	0.005 (0.002)
Ln(real investment) ³ * Ln(real capital stock) ²	-0.0004 0.0002
Ln(real investment) ³ * Ln(real capital stock) ³	0.000005 (0.000007)
Year dummies	Yes

Notes: The inverse mills ratio is derived from a sample of 166,576 establishments including the 103,664 in our main estimating sample that are observed for at least 5 years.

Source: authors' calculations using the ARD (Source: ONS).