Technological Catch-up and the Role of Multinationals

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Abstract

This paper investigates the importance of productivity catch-up, as an indicator of technology spillovers, to productivity growth. We find evidence that productivity catch-up is statistically and quantitatively important. Establishments in industries where high productivity firms have pushed out the technological frontier grow faster, indicating that leading firms generate positive externalities to non-frontier establishments. We find that both domestic and foreign-owned establishments play a leadership role. We quantify the contribution of affiliates of US multinationals to UK productivity growth by advancing the frontier. We also demonstrate that our empirical approach can encompass productivity dispersion in addition to technological catch-up between lagging and leading establishments.

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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 regulation[1] have revived interest in the subject. Foreign firms are viewed as conduits for technology transfer. The existing literature on externalities from foreign firms typically regresses productivity levels or growth rates on a measure of foreign presence in an industry, focusing on the impact of inward investment.[2] But recent work has emphasised the importance of technology sourcing - firms locating abroad in order to access the latest technologies and repatriate them to their home country.[3] The issue we address here is more general, in that we examine technological spillovers from any high productivity firm, not just those that are multinationals. In this paper we aim to shed light on the contribution of productivity catch-up, as an indicator of technological catch-up, to productivity growth. Within this we also examine the contribution that affiliates of US-owned multinationals make to UK productivity growth, through their role in advancing the industry technological frontier and enhancing the scope for productivity catch-up.US firms play an important role in the UK economy (accounting for around 25% of manufacturing employment).

Our empirical approach encapsulates firm heterogeneity, ongoing entry and exit, stochastic shocks to productivity, and endogenous productivity convergence to the technological frontier. We find evidence consistent with productivity catch-up to the technological fron-

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

[2] Measures used include the share of foreign firms in employment, sales, or the total number of firms. Aitken and Harrison (1999) use panel data on Venezuelan firms and find that there are no externalities to domestic firms from foreign investment; gains from foreign investment are fully captured by joint ventures. Other empirical studies include 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).

[3] Case 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 Reneen (2006) and Branstetter (2004).

tier and quantify the contribution of catch-up to productivity growth. We demonstrate that our findings are robust to a range of considerations including the presence of measurement error and mean reversion. In line with other research, we find evidence that US multinationals are frequently the most productive establishments and push out the technological frontier. We use our results to quantify their estimated contribution to productivity growth. However, we emphasise that domestic firms (in particular domestic multinationals sourcing technologies from abroad) can also be an important conduit for technology transfer.[4]

We also demonstrate that catch-up to the frontier is consistent with persistent productivity dispersion across establishments within industries. These results suggest an explanation for apparently contradictory strands of the existing research. Many empirical studies have emphasized the persistence of variation in productivity across establishments, even within narrowly defined industries.[5] These findings have prompted theoretical research modelling heterogeneity in productivity as the outcome of stochastic shocks or gradual learning about productivity.[6] However, a separate body of research has emphasized the importance of technological catch-up as a source of growth for those behind the technological frontier.[7] We show that heterogeneous productivity levels can emerge as an equilibrium outcome reflecting a tension between variation in establishments' innovative capabilities (which tends to increase dispersion) and productivity catch-up (which tends to reduce dispersion).

We apply these ideas using data on establishments located in the United Kingdom. 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

[4] See for example Doms and Jensen (1998), Griffith and Simpson (2004) and Criscuolo and Martin (2005) for empirical evidence that domestic multinationals frequently have comparable levels of productivity to their foreign-owned counterparts. See Griffith, Harrison and Van Reenen (2006) for evidence that UK multinationals are sourcing technologies from abroad.

[5] See, for example, 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).

[6] See for example Ericson and Pakes (1995), Hopenhayn (1992) and Jovanovic (1982).

[7] See, for example, Acemoglu *et al.* (2002), Aghion and Howitt (1997), Grossman and Helpman (1991), Howitt (2000) and Parente and Prescott (1994, 1999).

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 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. This historical background makes a UK a natural choice for exploring these ideas, although our empirical framework and results are of wider applicability.

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 to the technological frontier. To do this we use a formulation which captures convergence, 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 lnA, 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 technological frontier (A_{Fjt-1}) to capture convergence:

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

This specification has the following intuitive interpretation: the parameter γ_i captures an establishment's own rate of innovation through its underlying capabilities; the parameter λ captures the speed at which an establishment catches-up with the technological frontier; and u_{it} captures the influence of stochastic shocks to productivity growth.

In order to estimate this we take the first term on the right-hand side over to the left-hand side, and so consider TFP growth as a function of innovation and catch-up. We also allow for ongoing entry and exit such that an establishment exits if its productivity falls below a critical threshold A^*_{it}:

$$\begin{aligned} A_{it} &> A^*_{it} \qquad \text{enter / remain in the industry,} \\ A_{it} &\leq A^*_{it} \qquad \text{do not enter / exit the industry.} \end{aligned} \tag{2}$$

We discuss our empirical modelling of A^*_{it} below. Re-arranging equation (1), taking the first term on the right-hand side over to the left-hand side, we obtain:

$$\triangle \ln A_{it} = \gamma_i + \lambda \ln \left(\frac{A_{Fj}}{A_i} \right)_{t-1} + u_{it} \qquad \text{if} \qquad A_{it} > A^*_{it} \tag{3}$$

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 (3) 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 (3), 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 technological frontier A_{Fjt-1}, and thus indicates productivity catch-up, and does not simply reflect other phenomena such as mean reversion. We discuss this in section 4.4.

A final issue is that we can only estimate equation (3) on surviving establishments. We use the exit rule in equation (2) to control for the selection on surviving establishments, according to a standard Heckman (1976) selection correction. Failing to control for survival would potentially bias estimates of the parameters of interest. For example, if low productivity establishments are more likely to exit, failure to control for survival might lead to an overestimation of the speed of convergence, since only higher productivity establishments that converge in productivity towards the technological frontier are observed. As is standard in the existing empirical literature, we model firm's exit decision as a function of firm age, investment, capital stock, their interactions and higher-order terms in these variables (see for example Pavcnik 2003). The exclusion restriction is that these variables influence establishments' entry and exit decisions conditional on their productivity but do not directly influence productivity itself, which is consistent with our empirical framework (see also Ericson and Pakes 1995 and Olley and Pakes 1996). After estimating a probit regression for firm survival, we augment the equation for productivity growth in (3) with an inverse mills ratio to control for the non-random survival of establishments.

Our empirical model for productivity growth in equation (3) 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}:

$$u_{it} = T_t + \varepsilon_{it}. \tag{4}$$

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:

$$\ln A_{it} = \gamma_i + \alpha_1 \ln A_{it-1} + \alpha_2 \ln A_{Ft} + \alpha_3 \ln A_{Ft-1} + T_t + \varepsilon_{it}. \tag{5}$$

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.[8] The cointegrating relationship between non-frontier and frontier TFP above therefore has the following Equilibrium Correction Model (ECM) representation, with many attractive statistical properties:[9]

$$\triangle \ln A_{it} = \gamma_i + \beta \triangle \ln A_{Ft} + \lambda \ln \left(\frac{A_{Fj}}{A_i} \right)_{t-1} + T_t + \varepsilon_{it}, \tag{6}$$

where equation (3) is a more restrictive version of this expression, with $\beta = \alpha_2 = 0$ and $\lambda = (1 - \alpha_1)$.

[8]Under 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.

[9]See Hendry (1996).

2.1 Implications for productivity dispersion

Before proceeding to discuss the data and present our baseline empirical results, it is useful to examine the implications of this 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 equilibrium productivity dispersion.

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

$$\triangle \ln A_{Fjt} = \gamma_{Fj} + u_{Fjt}. \tag{7}$$

Combining the expression for the frontier above with the equation for TFP growth in a non-frontier establishment i in equation (3), yields an expression for the evolution of productivity in establishment i relative to the industry j frontier:

$$\Delta \ln \left(A_{it}/A_{Fjt} \right) = \left(\gamma_i - \gamma_{Fj} \right) + \lambda \ln \left(\frac{A_{Fjt-1}}{A_{it-1}} \right) + \left(u_{it} - u_{Fj} \right). \tag{8}$$

Taking expectations in equation (8) prior to the realization of the stochastic shock to technology, the error terms are equal to zero and the steady-state equilibrium level of technology relative to the frontier is:

$$\mathtt{E} \ \ln \left(\frac{\widehat{A_i}}{A_{Fj}} \right) = \frac{\gamma_i - \gamma_{Fj}}{\lambda}. \tag{9}$$

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 steady-state, the frontier will be whichever establishment in the industry has highest capability to innovate ($\gamma_{Fj} = \sup_i \{\gamma_i\}$). All other establishments will lie an equilibrium distance behind the frontier, such that expected productivity growth as a result of both innovation and catch-up equals expected productivity growth as a result of innovation in the frontier.

One of our empirical findings is that the affiliates of US multinationals frequently lie at the industry technological frontier. In terms of equation (9), this finding implies that affiliates of US multinationals often have higher levels of innovative capabilities (γ_i) than other multinationals and than purely domestic establishments. The higher innovative capabilities of US affiliates 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), (8) and (9) 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 technological frontier.

Although the establishment fixed effects are included in an equation for productivity *growth* (3), 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 (9).

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 technological frontier. More specifically, we focus on the *time-series* relationship between an establishment's productivity and productivity at the technological 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 (9), the cross-section sample standard deviation of productivity may rise, decline or remain constant over time.[10]

In summary, our empirical framework captures heterogeneity in productivity within industries, while allowing for endogenous productivity catch-up. Each establishment converges towards its own steady-state level of productivity relative to the industry technological frontier and there is equilibrium productivity dispersion. Stochastic shocks to technology induce ongoing entry and exit, and mean that establishments' productivities may depart from their steady-state equilibrium values for substantial periods of time. Convergence towards an establishment's steady-state equilibrium productivity relative to the frontier will occur gradually, depending on realizations of stochastic productivity shocks and the speed of productivity catch-up.

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

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

production technology.

The key assumptions behind the superlative index number measures that we employ are a constant returns to scale translog production function and perfect competition.[11] 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 TFP[12] 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.[13] 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 technological catch-up across establishments, which is a central feature of our empirical framework.

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

[11] See for example Caves et al. 1982a,b.

[12] Following the ideas in Hall (1988), Roeger (1995) and Klette (1999).

[13] While 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:

$$\triangle TFP_{it} = \triangle \ln Y_{it} - \sum_{z=1}^{Z} \tilde{\alpha}_{it}^z \triangle \ln x_{it}^z, \tag{10}$$

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.[14]

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:

$$\alpha_{it}^z = \xi_i + \sum_{z=2}^{Z} \phi_j^z \ln\left(\frac{x_{it}^z}{x_{it}^1}\right), \tag{11}$$

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 (10) and below. However, this correction in fact has little impact on our results.

[14] We 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,

$$MTFP_{it} = \ln\left(\frac{Y_{it}}{\bar{Y}_j}\right) - \sum_{z=1}^{Z} \sigma_i^z \ln\left(\frac{x_{it}^z}{\overline{x}_j^z}\right), \tag{12}$$

where a bar above a variable denotes a geometric mean; that is, $\bar{Y}_j$ and $\overline{x}_j$, 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 (11) 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 technological frontier in an industry-year. This is denoted by $TFPGAP_{it}$ and is the empirical counterpart to $\ln\left(A_j^F/A_i\right)_t$,[15]

$$TFPGAP_{it} = MTFP_{jt}^F - MTFP_{it}. \tag{13}$$

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.[16] We

[15] Note that equation (12) 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.

[16] Basic 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.[17] 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.[18] We include a sample selection correction

probability as weights to correct for this. For further discussion of the ARD see Griffith (1999), Oulton (1997) and Barnes and Martin (2002).

[17] Establishments 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.

[18] We drop very small 4-digit industries (with less than 30 establishments) in order to implement our proceedure 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 proceedures. 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.[19] 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.[20] 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 (12)) 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.

[19] Disney 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.

[20] Cameron, 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 technological frontier

Before turning to the econometric evidence it is worth considering what we are capturing in our measure of the distance to the technological frontier. We begin by using the establishment with the highest level of TFP to define the technological 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 technological frontier, as one establishment first catches up and then overtakes the establishment with the highest initial level of measured 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 technological 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 technological 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 technological 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 technological 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. Finally, we investigate the role that US-owned affiliates play in productivity catch-up by advancing the technological frontier.

4.1 Productivity dynamics

We start by correlating an establishment's distance to the technological frontier in their 4-digit industry, the technology gap term, with the establishment's TFP growth rate, 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 (3). 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 (3) and (9). 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.[21] 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 (3) 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 technological frontier in their 4-digit industry experience faster rates of productivity growth than firms that are more technologically advanced. 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 (9) 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

[21] Criscuolo 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).

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.

In the fourth column we add in the growth rate of TFP in the frontier, as in the ECM representation (equation 6). 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 (5)).

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 (3). Therefore, any measurement error in TFP_{it-1} would induce a spurious correlation between TFP growth and distance to the technological 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. These estimates are shown in column 5 of Table 3. We find that, conditional on differences that arise due to other covariates, establishments in the tenth decile (those furthest away from the technological frontier) experience 25% faster TFP growth that 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.[22]

We also take three further approaches. First, in column 1 of Table 4 we include an alternative measure of distance from the technological frontier, based on the average TFP in the five establishments with the highest measured TFP levels.[23] 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 technological 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 (3) 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

[22] We 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.

[23] This 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.

on longer lags.

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. The coefficient on the gap remains positive and significant, although the magnitude of the coefficient is somewhat reduced.

4.3 Parameter heterogeneity

Our baseline estimation results pool across industries, imposing common slope coefficients, and a concern we might have is that there might be parameter heterogeneity across industries - 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.[24] 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 technological 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 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.[25]

[24] See, for example, the discussion in Pesaran and Smith (1995).

[25] One 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 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 technological 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 technological 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 technological frontier, A_{Fjt-1}, also plays an important role.

In a first robustness test, we directly examine the importance of the position of the technological frontier by estimating the ADL(1,1) representation of our econometric equation in (5). 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 technological 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:

$$\triangle \ln A_{it} = \gamma_i + \lambda \ln A_{it-1} + u_{it}, \qquad |\lambda| < 1. \tag{14}$$

Under the null hypothesis that productivity catch-up plays an important role in determining establishment productivity growth, as in equation (3), the location of the technological frontier should also be important. We test this prediction by including the decile dummies in equation (14) 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, 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 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.[26]

Taken together, Table 5 provides evidence that our results cannot be simply explained by the alternative hypothesis of mean reversion. We find that the location of the technological frontier plays an important role in determining establishment productivity growth

[26] We 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.

in addition to the establishment's own level of productivity. Existing theoretical models of industry dynamics frequently assume that establishment productivities follow independent stochastic processes (e.g. Hopenhayn 1992, Jovanovic 1982, Ericson and Pakes 1995 and Melitz 2003). Our empirical findings concerning the importance of productivity catch-up suggest a richer process for the dynamics of establishment productivity. While innovative capabilities vary across establishments, and there is equilibrium productivity dispersion, lagging establishments may take advantage of opportunities to catch-up with leading establishments and converge towards the technological frontier.

4.5 Economic importance

It is important to emphasise that our results can only be interpreted as correlations that are consistent with productivity catchup. We do not directly measure technology transfer - what we find is that establishments that are further behind the technological frontier experience faster productivity growth than those that are near the frontier. This is consistent with technology transfer, and seems to be robust to a number of concerns. While these are only correlations, it is interesting to ask what these would estimates imply about the economic importance of productivity catch-up in growth, under the assumption that our interpretation is valid.

If we take the coefficient on the 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).[27]

As discussed above, if the affiliates of US multinationals have higher innovative capabilities (γ_i), they will frequently lie at the technological frontier within industries (equation (9)). The resulting expansion of the technological frontier raises productivity growth in non-frontier establishments by enhancing the opportunities for productivity catch-up. In the next section, we take this interpretation further and attempt to quantify this contribution of US affiliates to domestic productivity growth.

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.[28] Frequently, foreign-owned establishments may be close to, and may advance, the technological frontier within an industry, thereby providing a source of productivity catch-up for domestic-owned establishments. 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 question of whether US multinationals, through their

[27] If 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.

[28] For 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).

presence as techological leaders, have an additional impact on productivity growth.

We think of US-owned establishments as influencing the productivity growth of non-frontier establishments in so far as they advance the technological frontier. Table 6 quantifies this impact. We first show the extent to which US affiliates are present in the UK. Column 1 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 machinery and computer equipment, chemicals and instrument engineering, and make up the technological frontier over 25% of the time in these sectors.

The third column shows how far US-owned establishments advance the technological frontier, when they are the technological leader. Using our relative TFP measure we calculate the productivity gap between the US-owned frontier and the most technologically advanced 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 it advances it by 19%. To examine how important US establishments are in facilitating productivity catch-up for non-frontier UK-based establishments, we calculate the proportion of productivity catch-up ($\lambda TFPGAP_{it-1}$) due to US affiliates advancing the frontier ($\lambda \left(TFPGAP_{it-1} - TFPGAP^{*nf}_{it-1}\right)$), where $TFPGAP^{*nf}_{it-1}$ is a measure of what the productivity gap would have been if no US establishments had been present to advance the frontier, holding all else equal. This is equal to

$$\frac{\lambda\left(TFPGAP_{it-1}-TFPGAP^{*nf}_{it-1}\right)}{\lambda TFPGAP_{it-1}}=1-\frac{TFPGAP^{*nf}_{it-1}}{TFPGAP_{it-1}}.$$

We calculate this for each individual establishment and take the mean over all establishments. This is shown in column 4 of Table 6. We see that this 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 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 $TFPGAP_{it-1}$ 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. This is consistent with the idea that any high productivity firm can act as a conduit for productivity catch-up, not only foreign-owned multinationals. However, as shown above, our results imply that US-owned affiliates in the UK do play a significant role in productivity growth by shifting out the technological frontier.

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.

We also quantified the contribution of US multinationals to the growth of UK establishments through advancing the technological frontier, under the assumption that our results can be interpreted as implying technology spillovers. 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 have high levels of innovative capabilities and lie at the technological frontier. By advancing the technological frontier, US affiliates can therefore enhance the opportunities for lagging establishments to achieve growth through productivity catch-up. The magnitude of these externalities from productivity catch-up has become an important policy issue in the UK, where raising productivity is a central government objective and extensive sums of money have been expended to attract foreign firms. We find evidence consistent with a substantial contribution from US affiliates to domestic growth through productivity catch-up. This is larger in high-technology industries, such as mechanical engineering, instruments and office machinery and data processing equipment, where the US frequently exerts technological leadership.

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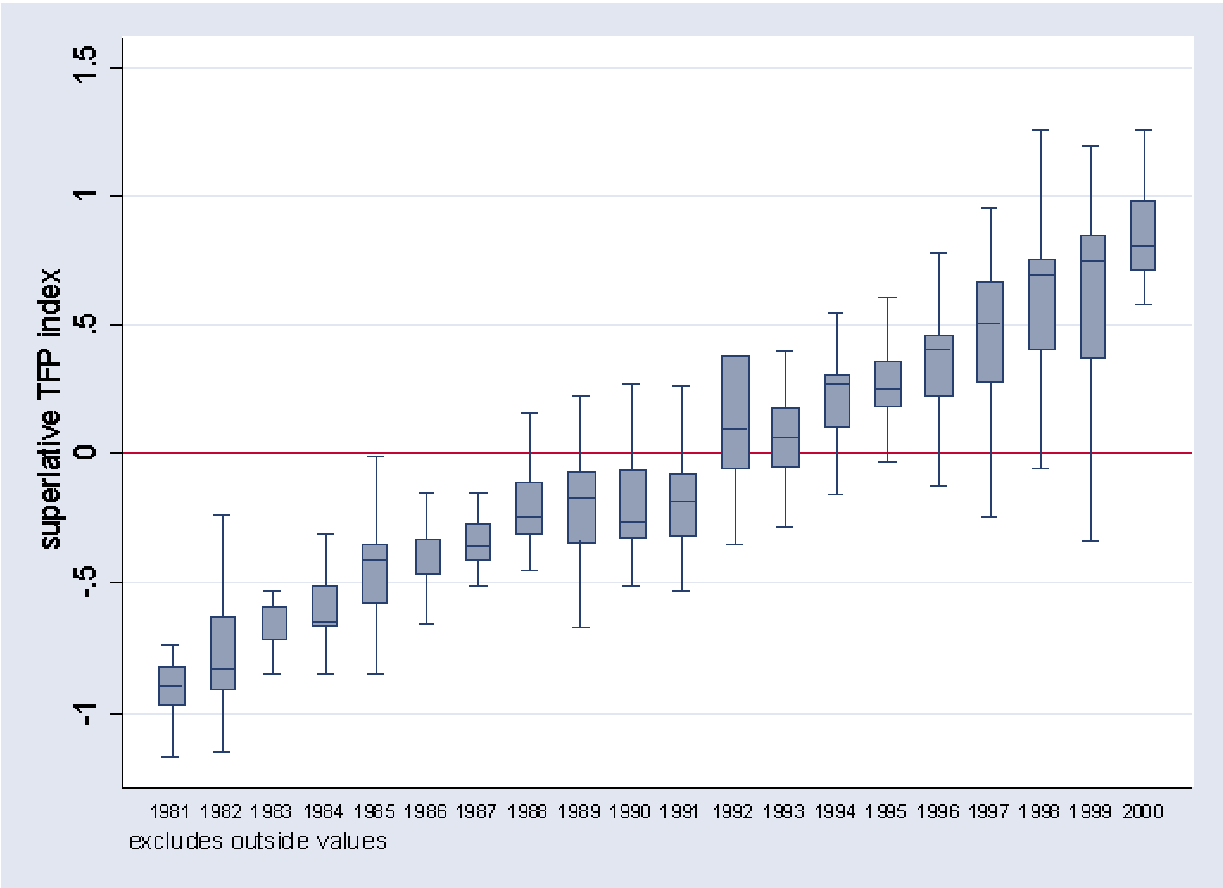
Table 1: Descriptive Statistics

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.

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

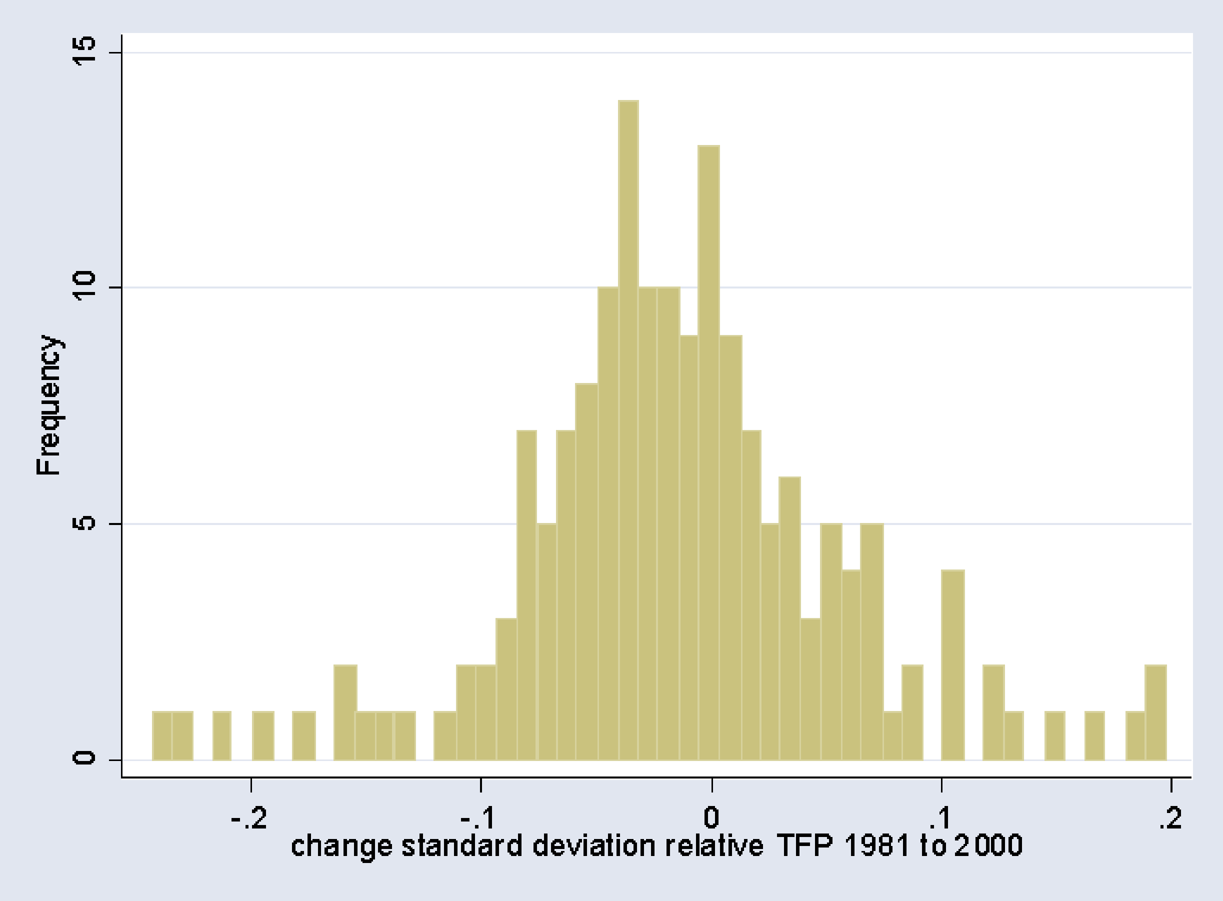


Note: The figure shows the distribution of TFP in 2-digit industry no.33 over time. TFP in each establishment is measured relative to the geometric mean of all other establishments in the same 4-digit industry (averaged over all years). The sample includes 627 observations on non-frontier establishments 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.

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.

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.

Table 2: Transition matrix

	Quintile of TFP distribution t					
Quintile of TFP distribution, t-5	1	2	3	4	5	Total
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.

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	0.091	0.117	0.199		0.134
	(0.012)	*(0.012)*	*(0.015)*	*(0.022)*		
Age		0.0002	0.0003	0.0002	0.001	0.0006
		(0.0005)	*(0.0006)*	*(0.0006)*	*(0.0004)*	
US dummy		0.005	0.007	0.010	0.007	0.013
		(0.002)	*(0.005)*	*(0.005)*	*(0.006)*	
Other foreign		-0.009	-0.020	-0.020	-0.022	-0.010
		(0.006)	*(0.014)*	*(0.014)*	*(0.015)*	
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	0.043	0.038	0.021	0.032
		(0.004)	*(0.010)*	*(0.011)*	*(0.012)*	
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.

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	0.138	0.054
		(0.070)	*(0.021)*	*(0.006)*
$TFPGAP5_{ijt-1}$	0.327			
	(0.030)			
Age	0.001	-0.0009	0.0005	0.0009
	(0.0006)	*(0.0008)*	*(0.001)*	*(0.0005)*
US dummy	0.004	0.012	-0.007	0.003
	(0.005)	*(0.006)*	*(0.009)*	*(0.005)*
Other foreign	-0.021	-0.031	-0.022	-0.015
	(0.015)	*(0.019)*	*(0.013)*	*(0.012)*
Inverse mills ratio	0.029	0.040	0.053	0.032
	(0.011)	*(0.021)*	*(0.018)*	*(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.

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	-0.342	-0.375	-0.271
	(0.036)	*(0.051)*	*(0.034)*	*(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	0.001	0.0005	-0.0004
	(0.0005)	*(0.0005)*	*(0.0006)*	*(0.0008)*
US dummy	0.006	0.006	0.010	0.010
	(0.005)	*(0.005)*	*(0.006)*	*(0.008)*
Other foreign dummy	-0.019	-0.021	-0.024	-0.025
	(0.017)	*(0.016)*	*(0.019)*	*(0.020)*
DD2		0.025	0.026	0.024
		(0.005)	*(0.007)*	*(0.007)*
DD3		0.039	0.042	0.041
		(0.009)	*(0.009)*	*(0.009)*
DD4		0.048	0.050	0.047
		(0.010)	*(0.010)*	*(0.010)*
DD5		0.058	0.060	0.057
		(0.010)	*(0.010)*	*(0.010)*
DD6		0.062	0.064	0.060
		(0.013)	*(0.011)*	*(0.010)*
DD7		0.068	0.069	0.065
		(0.015)	*(0.013)*	*(0.013)*
DD8		0.085	0.085	0.082
		(0.017)	*(0.014)*	*(0.013)*
DD9		0.087	0.093	0.089
		(0.021)	*(0.016)*	*(0.017)*
DD10		0.079	0.079	0.075
		(0.023)	*(0.019)*	*(0.020)*
Inverse mils ratio	0.006	0.006	-0.006	-0.005
	(0.015)	*(0.014)*	*(0.026)*	*(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.

Table 6: The 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
All manufacturing	*9*	*13*	*0.02*	*0.10*

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 $\ln(A_{F\ US}/ A_{F\ Non\text{-}US})$. 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.

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.