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TECHNOLOGICAL CATCH-UP AND GEOGRAPHIC PROXIMITY*

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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. Geographic proximity to frontier firms makes catch-up faster. Our econometric specification implies a long-run relationship between productivity levels, where nonfrontier 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 use our econometric estimates to quantify the implied contribution to productivity growth of catch-up to both the national and regional productivity frontiers.

1. INTRODUCTION

Deregulation and the opening of markets to international trade and investment have been widely recognized as major drivers of growth. Recent studies

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on entry regulation[1] 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 nonfrontier establishments. We also investigate whether geographic proximity matters, in the sense that firms benefit more from frontier establishments that are located nearby. We find that geographic proximity to frontier firms speeds up the process of catch-up. Using our econometric specification, we quantify the implied contribution to productivity growth of catch-up to both the national and regional productivity frontier.

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 order 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 nonfrontier 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, nonfrontier 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

[1]See, inter alia, Baily, Hulten, and Campbell (1992), Davis and Haltiwanger (1991), Nicoletti and Scarpetta (2002), Djankov et al. (2002), and Aghion et al. (2009).

[2]For 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).

[3]See 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 U.K. includes Haskel, Pereira, and Slaughter (2007), Girma and Wakelin (2002), Görg and Greenaway (2002), and Harris and Robinson (2002).

[4]Case studies emphasizing 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 (2006).

[5]The micro-econometric literature includes Baily et al. (1992), Bartelsman and Doms (2000), Davis and Haltiwanger (1991), Davis, Haltiwanger, and Schuh (1996), Disney, Haskel, and Heden (2003), Dunne, Roberts, and Samuelson (1989), and Foster, Haltiwanger, and Krizan (2002) among

both domestic and foreign firms in influencing the extent to which foreign presence contributes toward domestic productivity growth.[6] Our paper also contributes to the regional and urban economics literatures that emphasizes localized knowledge spillovers by providing evidence of regional productivity catchup to the frontier.[7]

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 United Kingdom lagged behind those of the United States. The 1980s saw a period of rapid growth in the United Kingdom that led to a reduction in the aggregate productivity gap with the United States. This aggregate picture hides substantial heterogeneity in productivity across establishments.

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 role of geographic proximity and the contribution to productivity growth of catch-up to the national and regional productivity frontier. The 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 characterize lnA, an index of technology or total factor productivity (TFP), as a function of its 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 for industry j (A_{Fjt-1}) to capture convergence:

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

others. For macroeconomic research on productivity convergence, see Acemoglu, Aghion, Zilibotti (2002), Aghion and Howitt (1997), Cameron (1996), Cameron, Proudman, and Redding (2005), Grossman and Helpman (1991), Howitt (2000), and Parente and Prescott (1994, 1999).

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

[7]The literature emphasizing localized knowledge spillovers dates back to at least Marshall (1920), as discussed by, for example, Krugman (1991), Duranton and Puga (2004), and Rosenthal and Strange (2004).

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:

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

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 nonfrontier 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 $\triangle \ln A_i$ and $ln(A_F/A_i)$ and Section 3.2 discusses our approach to productivity measurement and the 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 provide evidence 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 is not simply driven by variation in A_{it-1}, as discussed in Section 4.4.

A final issue is that we can only estimate equation (2) on surviving establishments. To control for the nonrandom 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 an unknown nonlinear function of firm age, log firm investment, and log firm capital stock, which have no direct effect on productivity under our assumptions of constant returns to scale and Hicks-neutral productivity differences. These firm characteristics are, therefore, suitable excluded variables from the productivity equation that affect the probability of firm survival.[8] As the functional form of the nonlinear relationship determining a firm's exit decision is unknown, we follow Olley and Pakes (1996) and Pavcnik (2002) in adopting a semiparametric specification, which approximates the unknown function using a polynomial expansion in firm age, log firm investment, log firm capital stock, and their interactions.

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 that begin far from the frontier and

[8]The correlation coefficients between these three variables are as follows: firm age and log investment (0.162), firm age and log capital stock (0.129), and log investment and log capital stock (0.756).

converge rapidly toward 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}:

$$u_{it} = T_t + \varepsilon_{it}. \tag{3}$$

Standard errors are clustered on four-digit industries, which allows the error term to be correlated across time within establishments and across establishments within four-digit industries (see, for example, Bertrand, Duflo, and Mullainathan 2004).[9]

As a robustness test, we consider an augmented version of this specification, which allows for a more flexible specification of the relationship between nonfrontier and frontier TFP, and which is derived from the following autoregressive distributed lag ADL(1,1) model for TFP levels:

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

Under the assumption of long-run homogeneity ($\frac{\alpha_2+\alpha_3}{1-\alpha_1} = 1$), which ensures that the rate of productivity catch-up depends on relative rather than absolute levels of productivity, we obtain the following equilibrium correction model (ECM) specification (see Hendry 1996):[10]

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

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

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.

[9]Bertrand et al. (2004) examine several approaches to allowing for correlated errors and show that clustering performs very well in settings with at least 50 clusters. While clustering on four-digit industries preserves a sufficiently large number of clusters, we also examined the robustness of our results to clustering on two-digit sectors, to allow, for example, for input–output linkages between industries within the same two-digit sector. While we find a similar pattern of results in this robustness check, we do not adopt it as our preferred specification, because of the relatively small number of clusters using two-digit sectors (around 20).

[10]Under the assumption of long-run homogeneity, 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.

Returning to our baseline specification for productivity growth in (2), the productivity frontier in industry j advances at a rate determined by innovative capabilities γ_{Fj} and a stochastic error u_{Fj}:

$$\triangle \ln A_{Fjt} = \gamma_{Fj} + u_{Fjt}. \tag{6}$$

Combining the expression for the frontier previously mentioned with the equation for TFP growth in a nonfrontier establishment i in equation (2) yields an expression for the evolution of productivity in establishment i relative to the industry j frontier:

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

Taking expectations in equation (7), the long-run equilibrium level of productivity relative to the frontier implied by our econometric specification is:

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

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 toward the constantly advancing frontier (λ is finite). In the long run, the frontier is whichever establishment in the industry has highest γ_i ($\gamma_{Fj} = \max_i\{\gamma_i\}$), while all other establishments lie a distance behind the frontier such that expected productivity growth including catch-up equals expected productivity growth in the frontier.

In our data we find that affiliates of U.S. multinationals frequently lie at the industry productivity frontier. In terms of equation (8), this finding implies that affiliates of U.S. 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 United Kingdom, and with the United States 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 nonfrontier 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 (our econometric specification is an ECM representation of this long-run relationship in productivity levels). 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).

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

3. DATA AND MEASUREMENT ISSUES

Measuring Growth and Relative Levels of TFP

As emphasized previously, one of the main challenges in the productivity literature is obtaining accurate measures of TFP growth and relative TFP 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 behavior we can allow a more flexible functional form for the 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] We therefore follow an influential line of research in assuming that the knowledge spillovers captured in our model of productivity catch-up are external to the firm, so that the firm's production technology exhibits constant returns to scale in its own inputs of labor and physical capital (see for example Fujita and Ogawa 1982, Lucas and Rossi-Hansberg 2002, and Combes et al. 2008). Following this line of research, we also assume that knowledge spillovers are disembodied and enter the Hicks-neutral productivity shifter in our model of productivity catch-up.[12] Together our assumptions of constant returns to scale and perfect competition 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 assumption of a 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[13] that allow for some form of imperfect competition where price

[11]See, for example, Caves, Christensen, and Diewert (1982a,b).

[12]Therefore this line of research abstracts from richer forms of knowledge spillovers that, for example, are nonneutral across the various factors of production such as capital, skilled, and unskilled workers.

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

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.[14] 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 ($\triangle TFP_{it}$, the empirical counterpart to $\triangle \ln A_{it}$) using the following superlative index number:

$$\triangle TFP_{it} = \triangle \ln Y_{it} - \sum_{z=1}^{Z} \tilde{\alpha}_{it}^{z} \triangle \ln x_{it}^{z}, \tag{9}$$

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 1 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.[15]

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:

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

[14]While other studies in the production function estimation literature consider translog functional forms following Christensen, Jorgensen, and Lau (1973), these studies do not typically allow for the endogeneity of factor input choices.

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

where ξ_i is an establishment-specific constant and where we have imposed constant returns to scale by normalizing 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 four-digit industries j. The fitted values from this equation are used as the factor shares in our calculation of (9) and below. While we make this correction to address potential concerns about measurement error, we in fact find a very similar pattern of results using the raw shares of factors of production in output.

The level of TFP in establishment i relative to the frontier in industry $j(TFPGAP_{it}$, the empirical counterpart to $\ln[A_j^F/A_i]_t)$ is measured using an analogous superlative index number. As a first step, 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,

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

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 by smoothing the factor shares using the properties of the translog production technology (see equation [10] previously mentioned), 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 our superlative index of the productivity gap between an establishment and the frontier in an industry-year ($TFPGAP_{it}$):[16]

$$TFPGAP_{it} = MTFP_{jt}^F - MTFP_{it}. \tag{12}$$

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 U.K. Office for National Statistics (ONS) and it is a legal obligation for firms to reply. These data provide us with information on inputs

[16]Note 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.

and output for production plants located in the United Kingdom.[17] We use data at the establishment level.[18] 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 four-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 four-digit industry level produced by the ONS. Price indices for investment in plant and machinery are available at the two-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 nonrandom responses. We use a cleaned up sample of establishments that conditions on establishments being sampled for at least five years.[19] As a robustness check, we examine the sensitivity of our results to alternative thresholds for the minimum number of years for which an establishment is present in the sample. To control for nonrandom survival of establishments, we include a sample selection correction term. As measurement error is likely to be larger in smaller establishments, we also weight observations by employment.

[17]Basic information (employment, ownership structure) is available on all plants located in the United Kingdom. Detailed data on inputs and outputs are 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 probability as weights to correct for this. For further discussion of the ARD see Griffith (1999) and Barnes and Martin (2002).

[18]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.

[19]We drop very small four-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 workers in output being between 0 and 1.

TABLE 1: Descriptive Statistics

Variable	Mean	Standard Deviation
$\Delta\, TFP_{ijt}$	0.003	0.129
$TFPGAP_{ijt-1}$	0.548	0.317
$\Delta\, TFP_{fjt}$	0.003	0.303
Age	8.127	5.122
U.S. dummy	0.120	0.325
Other foreign dummy	0.105	0.306

Note: The sample includes 103,664 observations on all nonfrontier 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).

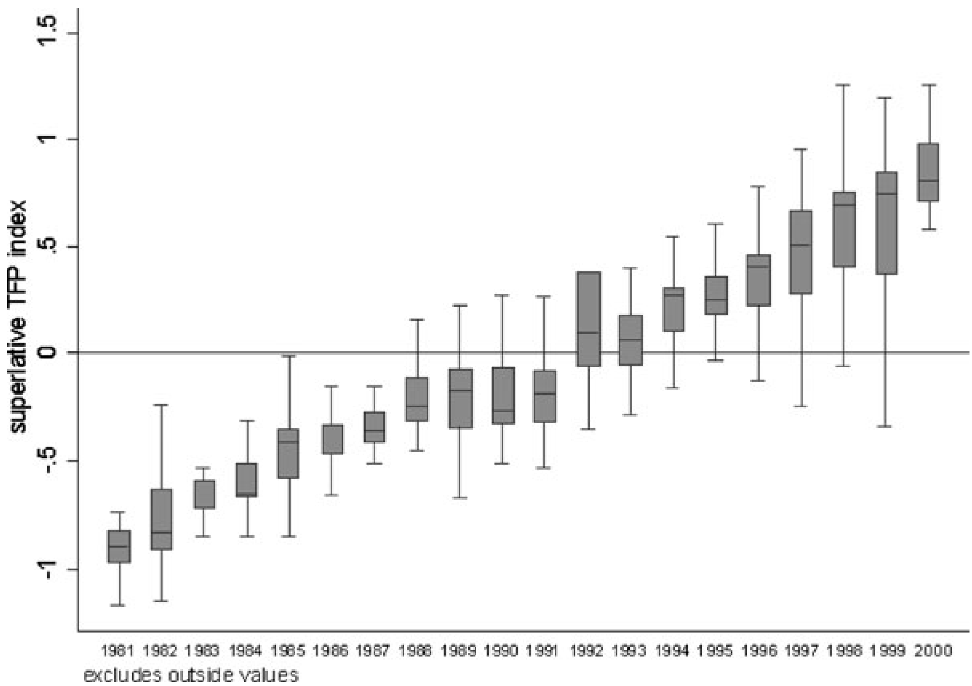
Productivity Growth and Dispersion

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 percent per annum over the period 1980 to 2000.[20] 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 United Kingdom and other countries.[21] Over this same period, labor productivity growth in our sample averaged 3.4 percent 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 examples of two-digit industries. Each year we plot the distribution between the 5th and 95th percentile, with the line in the middle of each gray 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 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 toward steady state, our empirical

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

[21] Cameron, Proudman, and Redding (1998) report negative estimated rates of TFP growth for some U.K. industries during 1970–1992, while Griliches and Lichtenberg (1984) report negative rates of TFP growth for some U.S. industries during an earlier period.



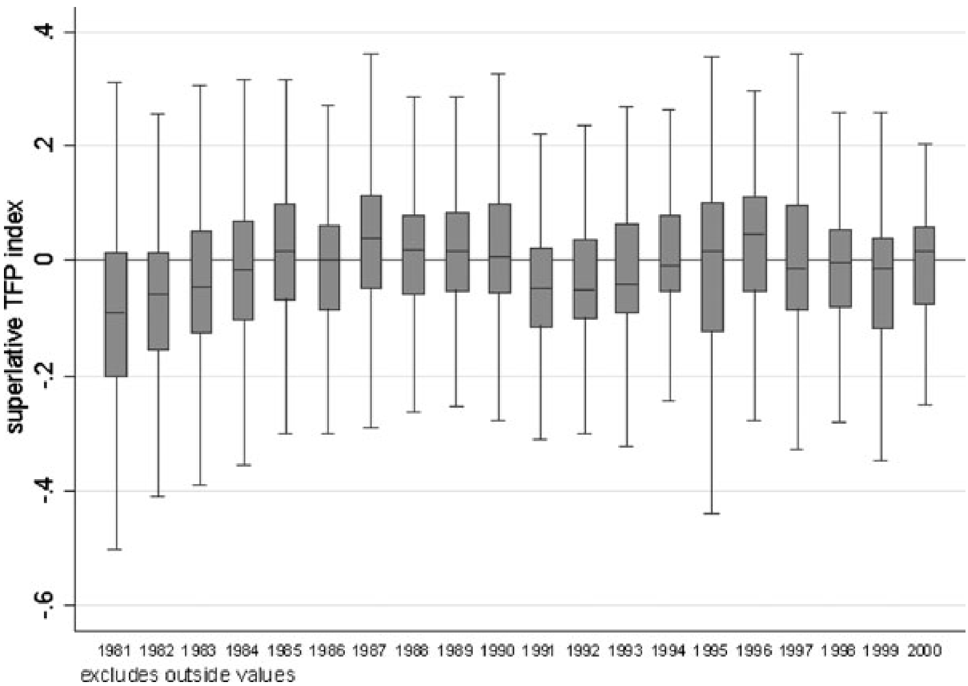
Note: The figure shows the distribution of TFP in two-digit industry no. 33 over time. TFP in each establishment is measured relative to the geometric mean of all other establishments in the same four-digit industry (averaged over all years). The sample includes 627 observations on nonfrontier establishments 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 1: Evolution of TFP in the Office Machinery and Computer Equipment Industry.

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 four-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 four-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 percent of those that survive have moved up to the top quintile, 24 percent have moved to the second quintile, 20 percent to the third, 21 percent to the fourth, and



Note: The figure shows the distribution of TFP in two-digit industry 45 over time. TFP in each establishment is measured relative to the geometric mean of all other establishments in the same four-digit industry (averaged over all years). The sample includes 6,129 observations on nonfrontier 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).

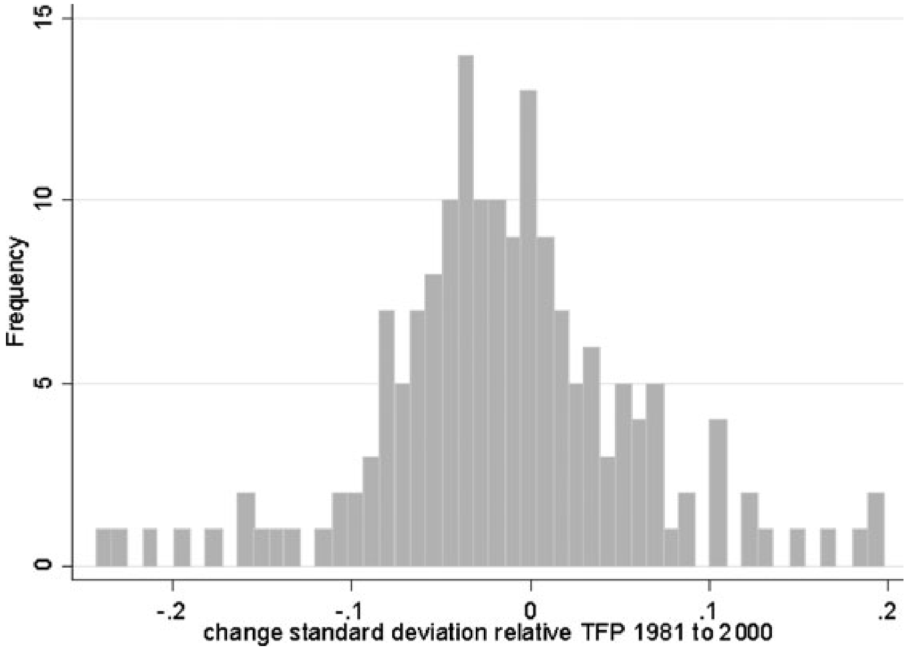
FIGURE 2: Evolution of TFP in the Footwear and Clothing Industry.

13 percent 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 previously.

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 previously provides one explanation for this, and subsequently we look at how well it describes the variation we see in the data.

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



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

FIGURE 3: Change in Standard Deviation of TFP Within Four-Digit Industries, 1981–2000.

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 four-digit industry in period $t-5$ and t, averaged over the four- to 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).

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 as discussed further subsequently.

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 percent higher than nonfrontier 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 relationship between TFP growth and an establishment's distance behind the frontier, and in doing so examine the role of geographic proximity. We then consider a number of robustness tests to address potential econometric concerns. We then use our estimates to quantify the importance of productivity catch-up to both the national and regional frontier in the growth process.

Productivity Dynamics

We start by examining the relationship between an establishment's TFP growth rate and distance to the TFP frontier in their four-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 U.S. 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 U.S.-owned establishments enters with a positive and significant coefficient, indicating that the U.K.-based affiliates of U.S. multinationals experience around a half of 1 percent faster growth than the average U.K. establishment. This is consistent with the idea that the affiliates of U.S. multinationals have higher levels of innovative capabilities (γ_i) in equations (2) and (8).[22] 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 U.S. multinationals that exhibit a statistically significant difference in innovative capabilities. This pattern of coefficients is consistent with other studies that have found U.S. multinationals are consistently more productive than other foreign-owned multinationals in the United Kingdom (see for example Griffith 1999 and Criscuolo and Martin 2005).[23] 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 four-digit industry have faster rates of productivity growth than firms closer to the frontier. This

[22]When we split the U.S. dummy into greenfield and acquisitions we find that the coefficient (standard error) on greenfield is 0.002 (0.002) and on acquisition is 0.007 (0.003). This is in line with other work using U.K. data, for example, Bloom, Sadun, and Van Reenen (2007).

[23]While U.S. multinationals account for the largest share of foreign-owned firms in the United Kingdom (12 percent of our sample, Table 1), we also included separate dummies for the three next largest inward investors Germany (1.5 percent of our sample), Canada (1.2 percent), and Switzerland (1.2 percent). The Canadian and Swiss dummies were statistically insignificant. The German dummy was negative but only marginally significant (at the 10 percent level).

TABLE 3: Catch-Up Model

Dep. Var: $\Delta\, TFP_{ijt}$	(1)	(2)	(3)	(4)	(5)	(6)
Obs	103,664	103,664	103,664	103,664	103,664	103, 664
$\Delta\, TFP_{Fjt}$				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*
Four-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 nonfrontier 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 four-digit industry 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 four-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 two-digit industry level regressions.

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

is consistent with the idea that there is productivity catch-up.[24] 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 (for example, 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.

While the increase in the coefficient on the productivity gap when fixed effects are included is consistent with a negative correlation between omitted establishment characteristics that raise the level of productivity and the productivity gap, we note that the inclusion of fixed effects and a lagged dependent variable leads to a downward bias in the estimated coefficient on the lagged dependent variable (Nickell 1981). Therefore, as $\ln A_{it} = (1-\lambda)\ln A_{it-1} + \lambda \ln A_{Fjt-1} + \gamma_i + u_{it}$ can be equivalently represented as $\ln A_{it} - \ln A_{it-1} = \lambda \ln A_{Fjt-1} - \lambda \ln A_{it-1} + \gamma_i + u_{it}$, the downward bias in the estimated value of $(1-\lambda)$ implies an upward bias in the estimated value of λ, which could also account for the rise in the estimated coefficient on the productivity gap between Columns 2 and 3. A comparison of the OLS estimates in Column 2 with the fixed effects estimates in Column 3 provides an indication of the potential magnitude of the bias, which is monotonically decreasing in the number of time-series observations in the panel.

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 nonfrontier 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 nonfrontier 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]).

The Importance of Geography

An interesting question is whether geographic proximity matters, in the sense that firms benefit more from frontier establishments that are located

[24]As a robustness check, we also re-estimated the specification in Column 3 clustering the standard errors on two-digit sector rather than four-digit industry, which has relatively little impact. For example the standard error on the productivity gap term becomes 0.019 rather than 0.015.

nearby. To investigate this, we extend our basic model by including a second TFP gap term, defined as an establishment's distance from the regional frontier, where the regional frontier is the establishment with the highest TFP in a particular geographic region, industry and year. We use two measures of geographic region: one is based on broad Government Administrative Regions (eight regions within England and Wales and Scotland), and the other is very detailed, covering around 300 Travel to Work Areas (TTWAs). TTWAs represent local labor market areas and are defined using information on individuals' commuting patterns, hence these should reflect better the geographic areas in which localized knowledge transfer might occur. For example, the three largest TTWAs in terms of total manufacturing employment in our data are the cities of London, Manchester, and Birmingham.

Table 4 shows details of mean TFP growth, the mean productivity gap with the overall frontier and the mean gap with the regional frontier. The first panel shows a breakdown by Administrative Region, and also provides information on the regional distribution of the overall frontier and all establishments. The second panel uses the TTWA definition of region. As the national frontier is the maximum of the regional frontiers, the average TFP gap with the regional frontier is smaller than that with the national frontier: 0.331 and 0.568, respectively, using Administrative Regions and 0.229 and 0.575, respectively, using TTWAs. There is however substantial variation in the size of the regional productivity gap.

In Table 5 we provide evidence that productivity catch-up varies with geographic proximity to the TFP frontier. The sample size is smaller than in Table 3 because information on location was only available for a restricted set of establishments (see note to Table 5), and since we also exclude those establishments identified as the regional frontier from the sample. In columns 1 and 4 of Table 5 we replicate the specification from column 3 of Table 3 to ensure that our main results are not substantially affected by the change in sample. In columns 2 and 5 we add in the measure of an establishment's distance to the regional TFP frontier to our main specification, and in columns 3 and 6 we include only the TFP gap with the regional frontier. The results using both the Administrative Region and TTWA definitions imply that establishments exhibit productivity catch-up both to the overall frontier and to the regional frontier. In particular, they are suggestive of faster catch-up to the regional frontier, consistent with the idea that knowledge spillovers may be to some extent geographically concentrated. Additionally, comparing the two panels of the table, we find that catch-up to the regional frontier is more rapid using TTWAs than Administrative Regions, which is consistent with the smaller size of TTWAs and the geographic localization of knowledge spillovers. Even though catch-up is faster to the regional frontier, we see that the overall national frontier still plays a role, and in Section 4.4 we examine the overall contribution to productivity growth of catch-up to each frontier.

TABLE 4: Descriptive Statistics at the Regional Level

	Mean TFP Growth (Standard Deviation) (1)	Gap with Overall Frontier (Standard Deviation) (2)	Gap with Regional Frontier (Standard Deviation) (3)	Number of Times Overall Frontier is in Region (% Total) (4)	Number Establishments (% Total) (5)
Administrative Region sample					
South East	0.002	0.549	0.411	731	19,879
	(0.126)	(0.288)	(0.269)	(25%)	(25%)
East Anglia	0.008	0.574	0.207	100	2,084
	(0.109)	(0.301)	(0.170)	(3%)	(3%)
South West	0.012	0.601	0.283	184	5,109
	(0.149)	(0.311)	(0.244)	(6%)	(6%)
West Midlands	0.007	0.534	0.301	313	11,973
	(0.113)	(0.273)	(0.213)	(11%)	(15%)
East Midlands	0.007	0.570	0.294	254	8,384
	(0.106)	(0.293)	(0.202)	(9%)	(11%)
Yorkshire and	0.008	0.560	0.297	287	9,112
Humberside	(0.105)	(0.288)	(0.222)	(10%)	(12%)
North West	0.005	0.547	0.308	419	10,337
	(0.125)	(0.297)	(0.244)	(15%)	(13%)
Northern	0.026	0.619	0.265	153	2,945
	(0.170)	(0.311)	(0.226)	(5%)	(4%)
Wales	0.016	0.629	0.277	143	3,034
	(0.130)	(0.310)	(0.220)	(5%)	(4%)
Scotland	0.018	0.663	0.380	299	6,217
	(0.167)	(0.345)	(0.330)	(10%)	(8%)
All	**0.008**	**0.568**	**0.331**	**2,883**	**79,074**
	(0.127)	**(0.298)**	**(0.251)**	**(100%)**	**(100%)**
TTWA sample					
All	**0.011**	**0.575**	**0.229**	**1,656**	**22,394**
	(0.126)	**(0.274)**	**(0.199)**	**(100%)**	**(100%)**

Note: Columns (1) to (3) are weighted by the inverse of the sampling probability and employment. Column (1) shows mean TFP growth of establishments in each region. Column (2) shows the mean gap with the frontier in the establishments' industry-year. Column (3) shows the mean gap with the frontier in the establishment's region-industry-year, where region is Administrative Region in the first panel and Travel to Work Area in the second panel. Column (4) shows the regional distribution of the national frontier establishments and column (5) shows the distribution of establishments used in the regressions in Table 5. See note to Table 5 for descriptions of each estimation sample.

Robustness

We present a number of robustness tests to examine potential econometric concerns. We consider three main robustness checks to address concerns

TABLE 5: Catch-Up to the Regional Frontier

	Administrative Regions			TTWAs		
Dep. Var: $\Delta\, TFP_{ijt}$	(1)	(2)	(3)	(4)	(5)	(6)
Obs	79,074	79,074	79,074	22,394	22,394	22,394
$TFPGAP_{ijt-1}$	0.131	0.082		0.162	0.112	
	(0.019)	*(0.013)*		*(0.032)*	*(0.026)*	
$TFPGAP\_REG_{ijt-1}$		0.111	0.163		0.173	0.234
		(0.017)	*(0.023)*		*(0.023)*	*(0.033)*
Agge	0.0002	0.0002	0.0003	−0.003	−0.002	−0.001
	(0.0007)	*(0.0006)*	*(0.0006)*	*(0.002)*	*(0.002)*	*(0.002)*
U.S. dummy	0.012	0.013	0.013	−0.0002	0.008	0.016
	(0.007)	*(0.008)*	*(0.009)*	*(0.012)*	*(0.011)*	*(0.012)*
Other foreign	−0.012	−0.011	−0.011	0.011	0.008	0.007
dummy	*(0.009)*	*(0.010)*	*(0.011)*	*(0.011)*	*(0.011)*	*(0.011)*
Inverse Mills ratio	0.045	0.040	0.038	0.045	0.032	0.021
	(0.011)	*(0.011)*	*(0.011)*	*(0.039)*	*(0.037)*	*(0.035)*
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Within groups	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.20	0.22	0.21	0.38	0.40	0.38

Note: Regressions are estimated on all nonfrontier establishments for 1980–2000 (columns [1] to [3]) and for 1984–1996 (columns [4] to [6]). Information on TTWAs is only available for a shorter period. All columns are weighted by the inverse of the sampling probability and employment. Standard errors in brackets are clustered at the four-digit industry. $\Delta\, TFP_{Fit}$ is TFP growth in the frontier. $TFPGAP_{ijt-1}$ is tfp relative to frontier in the previous period. $TFPGAP\_REG_{\cdot ijt-1}$ is TFP relative to the regional frontier (defined for 10 Administrative Regions or 300 TTWAs) in the previous period. Columns (1) and (4) replicate the specification from column (3) Table 3.

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

about measurement error and endogeneity, parameter heterogeneity, and mean reversion.

Measurement error

As mentioned previously, one concern is that TFP_{it-1} appears on both the right and left hand sides of our regression specification (2). Therefore measurement error in TFP_{it-1} could 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 previously). 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. 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 percent 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.[25]

We also take three further approaches. First, in column 1 of Table 6 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.[26] 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 6 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.

Second, another concern about measurement error is that TFP is measured under the assumption of perfect competition, as discussed previously. In column 3 of Table 6 we adjust the factor shares by an estimate of the markup (calculated at the two-digit industry-year level). The coefficient on the gap term remains positive and significant.

Third, in column 4 of Table 6 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.

Parameter heterogeneity and sample composition

Our baseline estimation results pool across industries, imposing common slope coefficients, and a possible concern is that there might be parameter

[25]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.

[26]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 in each industry-year.

TABLE 6: 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)*
U.S. 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		
		(0.000)		
F-statistics (P-value)				
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 nonfrontier 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 four-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 two-digit industry–year level. In column (4) we use Olley–Pakes'Pavnick estimates of TFP.

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

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 two-digit industry.[27] As shown in column 6 of Table 3, this yielded a similar pattern of results. The median estimated coefficients, across two-digit industries, were 0.134 for distance from the productivity frontier, 0.0006 for age, 0.013 for the U.S. 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 two-digit industries it was significant at the 5 percent level.

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

These estimates lie close to the baseline within groups estimates reported in column 3 of Table 3.[28]

As a further robustness check, we examined the sensitivity of our results to outliers. To do so, we followed the conventional approach of using the residuals to classify observations as influential if they have a DFITS of greater than two multiplied by the square root of the number of regressors/number of observations. Excluding observations classified as influential we find a very similar pattern of results, with an estimated coefficient (standard error) of 0.087 (0.005) on the productivity gap, lying close to our baseline estimate reported in column 3 of Table 3.

Finally, we also examine the sensitivity of our results to alternative thresholds for the minimum number of years for which an establishment is present in the data. Re-estimating our baseline specification requiring establishments to be observed for a minimum of 10 years results in a similar estimated coefficient (standard error) on the productivity gap of 0.109 (0.016). This similarity of the results despite a substantial reduction in the sample size suggests that our findings are not highly sensitive to the minimum number of years over which an establishment is observed in the data.

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.

To address this concern, we test the null hypothesis that each establishment reverts to its own mean level of TFP by examining the statistical significance of the decile dummies used above. Under this null hypothesis,

[28]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 the specification is estimated separately for each two-digit industry, allow for separate time effects for each two-digit industry. In addition, we ran the specification with deciles (column 5 of Table 3) including four-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).

establishment TFP follows an AR(1) process with reversion to an establishment specific mean:

$$\triangle \ln A_{it} = \gamma_i + \lambda \ln A_{it-1} + u_{it}, \qquad |\lambda| < 1. \tag{13}$$

Under the alternative 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 1 of Table 7, 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 2. 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 3 returns to the AR(1) specification from column 1, 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.[29] 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.

Economic Importance

What do our results imply about the magnitude of the contribution of productivity catch-up to productivity growth in nonfrontier 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 percent of annual growth, (taking the mean across establishments, rather than the median we find that productivity catch-up accounts for on average 8 percent 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 percent of growth

[29] 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.

TABLE 7: Further Robustness

	(1)	(2)	(3)
Dependent Variable	$\Delta\, TFP_{ijt}$	$\Delta\, TFP_{ijt}$	$\Delta\, TFP_{ijt}$
Obs	103,664	84,232	70,023
TFP_{ijt-1}	−0.342	−0.375	−0.271
	(0.051)	*(0.034)*	*(0.035)*
TFP_{ijt-2}		0.068	
		(0.016)	
Age	0.001	0.0005	−0.0004
	(0.0005)	*(0.0006)*	*(0.0008)*
U.S. dummy	0.006	0.010	0.010
	(0.005)	*(0.006)*	*(0.008)*
Other foreign dummy	−0.021	−0.024	−0.025
	(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 Mills ratio	0.006	−0.006	−0.005
	(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
Within groups	Yes	Yes	Yes
R^2	0.307	0.310	0.318

Notes: Regressions are estimated on nonfrontier 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 four-digit industry. In column (3) we instrument TFP_{t-1} with TFP_{t-2} and TFP_{t-3}.

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

(taking the mean across establishments, productivity catch-up accounts for 98 percent of annual predicted productivity growth).[30]

We can also use the specifications in columns 2 and 5 of Table 5 to examine the contribution of catch-up to the national versus regional frontier to productivity growth. Using the approach described previously, the estimates from column 2 imply that for the median establishment catch-up to the national frontier accounts for 13 percent of annual productivity growth (43 percent of predicted growth) and catch-up to the Administrative Region frontier 5 percent of annual productivity growth (18 percent of predicted growth). Similarly, for column (5) for the median establishment catch-up to the national frontier accounts for 19 percent of annual productivity growth (44 percent of predicted growth) and catch-up to the Travel to Work Area frontier 3 percent of annual productivity growth (11 percent of predicted growth). Hence, while the results in Table 5 demonstrate that geographic proximity to a frontier establishment implies faster productivity catch-up, because the productivity gap with the regional frontier is smaller than with the national frontier, (as shown in Table 4), the overall contribution to productivity growth of catch-up to the regional frontier is smaller.

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. We also found evidence that geographic proximity makes the catch-up process faster. Taken together, our findings suggest 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.

[30]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.

REFERENCES

Acemoglu, D., P. Aghion, and F. Zilibotti. 2006. "Distance to Frontier, Selection, and Economic Growth," *Journal of the European Economic Association*, 4(1), 37–74.

Aghion, P., R. Blundell, R. Griffith, P. Howitt, and S. Prantl. 2009. "The Effects of Entry on Incumbent Innovation and Productivity," *Review of Economics and Statistics*, 91(1), 20–32.

Aghion, P. and P. Howitt. 1997. *Endogenous Growth Theory*, Cambridge, MA: MIT Press.

Aitken, B. and A. Harrison. 1999. "Do Domestic Firms Benefit from Direct Foreign Investment? Evidence from Venezuela," *American Economic Review*, 605–618.

Baily, N., C. Hulten, and D. Campbell. 1992. "Productivity Dynamics in Manufacturing Plants," *Brookings Papers on Economic Activity*, Microeconomics, 187–267.

Baily, M. and A. Chakrabarty. 1985. "Innovation and Productivity in US Industry," *Brookings Papers on Economic Activity*, 2, 609–632.

Bartelsman, E. and M. Doms. 2000. "Understanding Productivity: Lessons from Longitudinal Microdata," *Journal of Economic Literature*, XXXVIII, 569–594.

Bernard, A. and C. Jones. 1996. "Comparing Apples to Oranges: Productivity Convergence and Measurement Across Industries and Countries," *American Economic Review*, 1, 216–238.

Bertrand, M., E. Duflo, and S. Mullainathan. 2004. "How Much Should we Trust Differences in Differences Estimates?," *Quarterly Journal of Economics*, 119(1), 249–275.

Bloom, N., R. Sadun and J. Van Reenen. 2007. "Americans Do I.T. Better: US Multinationals and the Productivity Miracle," NBER Working Paper No. 13085, May 2007.

Blomstrom, M. 1989. *Foreign Investment and Spillovers*, Routledge: London.

Branstetter, Lee. 2006. "Is Foreign Direct Investment a Channel of Knowledge Spillovers: Evidence from Japan's FDI in the United States," *Journal of International Economics*, 68, 325–344.

Cameron, G. 2005. "The Sun Also Rises: Productivity Convergence between the USA and Japan," *Journal of Economic Growth*, 10(4), 387–408.

Cameron, G., J. Proudman, and S. Redding. 2005. "Technology Transfer, R&D, Trade and Productivity Growth," *European Economic Review*, 49(3), 775–807.

Caves D., L. Christensen, and E. Diewert. 1982a. "The Economic Theory of Index Numbers and the Measurement of Input, Output and Productivity," *Econometrica*, 50(6), 1393–1414.

——. 1982b. "Multilateral Comparisons of Output, Input and Productivity Using Superlative Index Numbers," *Economic Journal*, 92, 73–86.

Combes P.-P., G. Duranton, L. Gobillon, D. Puga, and S. Roux. 2008. "*The Productivity Advantages of Large Cities: Distinguishing Agglomeration from Firm Selection*," mimeograph, University of Toronto.

Christensen L., D. Jorgenson, and L. Lau. 1973. "Transcendental Logarithmic Production Frontiers," *Review of Economics and Statistics*, 55(1), 28–45.

Criscuolo, C. and R. Martin. 2005. "Multinationals, and US Productivity Leadership: Evidence from Britain," *Review of Economics and Statistics*, 92(2), 263–281.

Cohen, W.M. 1995. "Empirical Studies of Innovative Activity," in P. Stoneman, (ed.), *Handbook of the Economics of Innovation and Technical Change*. Oxford: Basil Blackwell.

Davis, S.J. and J.C. Haltiwanger. 1991. "Wage Dispersion between and within U.S. Manufacturing Plants, 1963-86," *Brookings Papers on Economic Activity*, Microeconomics, 115–180.

Davis, S.J., J.C. Haltiwanger, and S. Schuh. 1996. *Job Creation and Destruction*, Cambridge, MA: MIT Press.

Disney, R., J. Haskel, and Y. Heden. 2003. "Restructuring and Productivity Growth in UK Manufacturing," *Economic Journal*, 113(489), 666–694.

Djankov, S., R. La Porta, F. Lopez-de-Silanes, and A. Shleifer. 2002. "The Regulation of Entry," *Quarterly Journal of Economics*, CXVII, 1–37.

Doms, M. and J.J. Bradford. 1998. "Comparing Wages, Skills, and Productivity between Domestically and Foreign-Owned Manufacturing Establishments in the United States," in R. Baldwin, et al. (eds), *Geography and Ownership as Bases for Economic Accounting*, Chicago, IL: University of Chicago Press, pp. 235–258.

Duranton, G. and D. Puga. 2004. "Micro-Foundations of Urban Agglomeration Economies," in J.V. Henderson and J.-F. Thisse (eds), *Handbook of Regional and Urban Economics Volume 4: Cities and Geography.* Amsterdam, The Netherlands: Elsevier, pp. 2063–2117.

Dunne, T., M.J. Roberts, and L. Samuelson. 1989. "The Growth and Failure of U.S. Manufacturing Plants," *Quarterly Journal of Economics*, 104(4): 671–698.

Ericson, R. and A. Pakes. 1995. "Markov-Perfect Industry Dynamics: A Framework for Empirical Work," *Review of Economic Studies*, 62, 53–82.

Foster, L., J. Haltiwanger, and C. Krizan. 2002. "The Link between Aggregate and Micro Productivity Growth: Evidence from Retail Trade," *NBER Working Paper*, #9120.

Fujita, M. and H. Ogawa. 1982. "Multiple Equilibria and Structural Transition of Non-monocentric Urban Configurations," *Regional Science and Urban Economics*, 12, 161–196.

Girma, S. and K. Wakelin. 2002. "Are There Regional Spillovers from FDI in the UK?" in *Trade, Investment and Labour: Proceedings of IEA Conference on Globalisation and Labour Markets*, D. Greenaway, R. Upward and K. Wakelin (eds.), Basingstoke, Hampshire, England: Palgrave.

Girma, S., D. Greenaway, and K. Wakelin. 2001. "Who Benefits from Foreign Direct Investment in the UK?" *Scottish Journal of Political Economy*, 48, 19–33.

Girma, S. 2005. "Absorptive Capacity and Productivity Spillovers from FDI: A Threshold Regression Analysis," *Oxford Bulletin of Economics and Statistics*, 67(3), 281–306.

Girma, S. and H. Gorg. 2007. "Evaluating the Foreign Ownership Wage Premium using a Difference-in-Differences Matching Approach," *Journal of International Economics*, 72(1), 97–112.

Globerman, S. 1979. "Foreign Direct Investment and Spillover Efficiency Benefits in Canadian Manufacturing Industries," *Canadian Journal of Economics*, 12, 42–56.

Görg, H. and D. Greenaway. 2004. "Much Ado About Nothing? Do Domestic Firms Really Benefit from Foreign Direct Investment?" *World Bank Research Observer*, 19(2), 171–197.

Görg, H. and E. Strobl. 2001. "Multinational Companies and Indigenous Development: An Empirical Analysis," *European Economic Review*, 46(7), 1305–1322.

Griffith, R. 1999. "Using the ARD Establishment-level Data to Look at Foreign Ownership and Productivity in the United Kingdom," *Economic Journal*, 109, F416–F442.

Griffith, R., R. Harrison, and J. Van Reenen. 2006. "How Special is the Special Relationship? Using the Impact of US R&D Spillovers on UK Firms as a Test of Technology Sourcing," *American Economic Review*, 96(5), 1859–1875.

Griffith, R. and H. Simpson. 2004. "Characteristics of Foreign-Owned Firms on UK Manufacturing Productivity," in R. Blundell, D. Card, and R. Freeman (eds.), *Creating a Premier League Economy*, Chicago, IL: The University of Chicago Press.

Griffith, R., S. Redding, and J. Van Reenen. 2004. "Mapping the Two Faces of R&D: Productivity Growth in a Panel of OECD Industries," *Review of Economics and Statistics*, 86(4), 883–895.

Griliches, Z. 1992. "The Search for R&D Spillovers," *The Scandinavian Journal of Economics*, 94, 29–47.

Griliches, Z. and F. Lichtenberg. 1984. "R&D and Productivity Growth at the Industry Level: Is There Still a Relationship?" in Z. Griliches (ed.), *R&D, Patents and Productivity*, NBER and Chicago University Press.

Grossman, G. and E. Helpman. 1991. *Innovation and Growth in the Global Economy*, Cambridge, MA: MIT Press.

Hall, R. 1988. "The Relationship between Price and Marginal Cost in US Industry," *Journal of Political Economy*, 96(5), 921–947.

Harrigan, J. 1997. "Technology, Factor Supplies and International Specialisation," *American Economic Review*, 87, 475–494.

Harris, R. and C. Robinson. 2004. "Spillovers from Foreign Ownership in the United Kingdom: Estimates for UK Manufacturing Using the ARD," *National Institute Economic Review*, 58–75.

Haskel, J., S. Pereira, and M. Slaughter. 2007. "Does Inward Foreign Direct Investment Boost the Productivity of Domestic Firms?" *The Review of Economics and Statistics*, Vol. 89(3), pp. 482–496, Cambridge, MA: MIT Press.

Heckman, J. 1976. “The Common Structure of Statistical Models of Truncation, Sample Selection, and Limited Dependent Variables and a Simple Estimator for Such Models,” *Annals of Economic and Social Measurement*, 5, 475–492.

Hendry, D. 1996. *Dynamic Econometrics*. Oxford: Oxford University Press.

Helpman, E., M. Melitz, and S. Yeaple. 2004. “Export Versus FDI With Heterogeneous Firms,” *American Economic Review*, 300–316.

Hopenhayn, H. 1992. “Entry, Exit, and Firm Dynamics in Long-Run Equilibrium,” *Econometrica*, 60(5), 1127–1150.

Howitt, P. 2000. “Endogenous Growth and Cross-country Income Differences,” *American Economic Review*, 90(4), 829–846.

Jovanovic, B. 1982. “Selection and the Evolution of Industry,” *Econometrica*, 50(3), 649–670.

Keller, W. 2004. “International Technology Diffusion,” *Journal of Economic Literature*, 42(3), 752–782.

Keller, W. and S. Yeaple. 2003. “Multinational Enterprises, International Trade, and Productivity Growth: Firm-Level Evidence from the United States,” *NBER Working Paper*, #9504.

Kinoshita, Y. 2001. “R&D and Technology Spillovers Through FDI: Innovation and Absorptive Capacity,” *CEPR Discussion Paper*, 2775.

Klette, T. and Z. Griliches. 1996. “The Inconsistency of Common Scale Estimators When Output Prices are Unobserved and Endogenous,” *Journal of Applied Econometrics*, 11(4), 343–361.

Krugman, P. 1991. *Geography and Trade*, Cambridge, MA: MIT Press.

Levinsohn, J. and A. Petrin. 2003. “Estimating Production Functions using Inputs to Control for Unobservables,” *Review of Economic Studies*, 70, 317–341.

Lucas, R.E. and E. Rossi-Hansberg. 2002. “On the Internal Structure of Cities,” *Econometrica*, 70(4), 1445–1476.

Markusen, J. 2002. *Multinational Firms and the Theory of International Trade*, Cambridge: MIT Press.

Marshall, A. 1920. *Principles of Economics*, London: Macmillan.

Melitz, M.J. 2003. “The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity,” *Econometrica*, 71, 1695–1725.

Nickell, S. 1981. “Biases in Dynamic Models with Fixed Effects,” *Econometrica*, 49(6), 1,417–26.

Nicoletti, G. and S. Scarpetta. 2003. “Regulation, Productivity and Growth: OECD Evidence,” *OECD Economics Department Working Paper*, 347.

Olley, S. and A. Pakes. 1996. “The dynamics of Productivity in the Telecommunications Equipment Industry,” *Econometrica*, 64(6), 1263–1297.

Parente, S. and E. Prescott. 1994. “Barriers to Technology Adoption and Development,” *Journal of Political Economy*, 102(2), 298–321.

Parente, S. and E. Prescott. 1999. “Monopoly Rights: A Barrier to Riches,” *American Economic Review*, 89(5), 1216–1233.

Pavcnik, N. 2002. “Trade Liberalization, Exit, and Productivity Improvements: Evidence form Chilean Plants,” *Review of Economic Studies*, 69, 245–276.

Pesaran, H. and R. Smith. 1995. “Estimating Long-Run Relationships from Dynamic Heterogeneous Panels,” *Journal of Econometrics*, 68, 79–113.

Roeger, W. 1995. “Can Imperfect Competition Explain the Difference between Primal and Dual Productivity Measures? Estimates for US Manufacturing,” *Journal of Political Economy*, 103(2), 316–330.

Romer, P. 1990. “Endogenous Technological Change,” *Journal of Political Economy*, 98(5), S71–S102.

Rosenthal, S.S. and W.C. Strange. 2004. “Evidence on the Nature and Sources of Agglomeration Economies,” in V. Henderson and J. Thisse (eds.), *Handbook of Regional and Urban Economics Volume 4: Cities and Geography*, Amsterdam, The Netherlands: Elsevier.

Serapio, M. and D. Dalton. 1999. "Globalization of industrial R&D: an examination of foreign direct investments in R&D in the United States," *Research Policy*, 28, 303–316.

Javorcik, S.B. 2004. "Does Foreign Direct Investment Increase the Productivity of Domestic Firms? In Search of Spillovers through Backward Linkages," *American Economic Review*, 94(3), 605–627.

Teece, D. 1977. "Technology transfer by multinational firms: the resource cost of transferring technological know-how," *Economic Journal*, 87(346), 242–261.

von Zedtwitz, M. and O. Gassmann. 2002. "Market versus Technology Drive in R&D Internationalization: Four Different Patterns of Managing Research and Development," *Research Policy*, 31, 569–588.

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)

Continued

TABLE A1: Continued

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 fq 1,664 in our main estimating sample that are observed for at least five years.

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