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Absorptive capacity and productivity spillovers from FDI: a threshold regression analysis

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Absorptive capacity and productivity spillovers from FDI: a threshold regression analysis

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Abstract

The influence of absorptive capacity in productivity spillovers from FDI is explored using recently developed threshold regression techniques. These characterise technology transfer as a non-linear process where the impact of FDI could either be negative, positive or neutral, depending on some critical values of the absorptive capacity distribution. Substantial heterogeneity in the way FDI-induced externalities are distributed across domestic firms in the U.K. is uncovered. There are also additional findings on the importance of exporting , geographic proximity and the motivation of FDI.

Outline

Non-Technical Summary

Does a domestic firm need to possess a minimum level of technological capacity to benefit from foreign firms' stock of knowledge? Economic theory gives conflicting answers. Some models predict that a greater technological or absorptive capacity increases spillovers benefits from FDI; others postulate that the rate of externality from FDI is maximised when the technology gap between domestic and foreign firms is greatest. The purpose of this paper is to empirically examine the nature of the absorptive capacity-technology spillovers nexus, using firm-level data from the U.K. manufacturing industry, over the period 1989-1999. In doing so it adds to the existing literature in three ways. First and foremost, it applies, for the first time in this context, threshold regression techniques that characterise technology transfer as a non-linear process where the impact of FDI could either be negative, positive or neutral, depending on some critical values of the absorptive capacity distribution Second, it investigates the impact of exporting on absorptive capacity and productivity spillovers from both regional and extra-regional FDI. Third, it attempts to test the conjecture that the nature of the externalities associated with FDI depends upon the foreign firm's particular motivation for undertaking it.

The analysis yields three main conclusions. First, more absorptive capacity generally speeds up the rate of technology externality from multinationals. Initially FDI-induced productivity gains increase at an increasing rate, but the rate diminishes as the absorptive capacity of domestic firms increases. It appears that the marginal effect of FDI on the productivity trajectories of firms with an already high technological capacity is less important. But there also appears to be a minimum absorptive capacity threshold below which the magnitudes of productivity spillovers are non-existent or even negative. Second, productivity spillovers have geographical dimensions, in the sense that they are more pronounced in the region the FDI takes place. But we uncover evidence that exporters have the potential to overcome the constraints of geographical distance. Third, technology spillovers tend to occur in sectors where FDI is motivated by traditional asset-exploiting considerations. Economically significant externalities due to multinationals that are chiefly motivated by the desire to get close to technological assets located in the U.K. are few and far between.

1. Introduction

Does a domestic firm need to possess a minimum level of technological capacity to benefit from foreign firms' stock of knowledge? Economic theory gives conflicting answers. Lapan and Bardhan (1973) argue that firms need a certain absorptive capacity before they can benefit from new technologies discovered by other firms. Cohen and Levinthal (1989) maintain that increased R&D activities help boost efficiency indirectly, because these activities speed up the assimilation of technologies developed outside the domestic sector. By contrast, Findlay (1978) puts forwards the hypothesis that the rate of technological externality from FDI is an increasing function of the technology gap between the 'backward' region and the 'advanced' region. In the same vein, the model of Wang and Blomström (1992) predicts a positive relationship between the degree of spillovers from FDI and the size of the technology gap between foreign and domestic firms.

The purpose of this paper is to econometrically examine the nature of the absorptive capacity-technology spillovers nexus, using firm-level data from the U.K. manufacturing industry over the period 1989-1999. In doing so it adds to the existing empirical literature in three ways. First and foremost, it applies, for the first time in this context, Hansen's (2000) threshold regression techniques. These characterise technology transfer as a non-linear process where the impact of FDI could either be negative, positive or neutral, depending on some critical values of the absorptive capacity distribution. Second, it investigates the impact of exporting on absorptive capacity and productivity spillovers from both regional and extra-regional FDI. Third, it attempts to test the conjecture by Cantwell and Narula (2001) that the nature of the externalities associated with FDI depends upon the foreign firm's particular motivation for undertaking it. In this respect, this study complements the initial contribution of Driffield and Love (2001) which is based on industry-aggregated data.

Our analysis yields three main conclusions. First, more absorptive capacity generally speeds up the rate of technology externality from multinationals. Initially FDI-induced productivity gains increase at an increasing rate, but the rate diminishes as the absorptive capacity of domestic firms increases. It appears that the marginal effect of FDI on the productivity trajectories of firms with an already high technological capacity is less important. But there also appears to be a minimum absorptive capacity threshold below which the magnitudes of productivity spillovers are non-existent or even negative. Second, productivity spillovers have geographical dimensions, in the sense that they are more pronounced in the region the FDI takes place. But we uncover evidence that exporters have the potential to overcome the constraints of geographical distance. Third, technology spillovers tend to occur in sectors where FDI is motivated by traditional asset-exploiting considerations. Economically significant externalities due to, in the words of Fosfuri and Motta (1999), `multinationals without advantages', are few and far between.

The remainder of the paper starts with a brief review of recent empirical studies linking FDI spillovers with spatial distance and technological capability. In Section 3 we present the threshold model, and outline the estimation strategy. Section 4 gives a description of the basic characteristics of the data. The main empirical findings are presented in Section 5. The last section concludes.

2: **A review of recent literature**

The theoretical basis for the expectation of spillovers from foreign firms is the level of firm-specific assets that MNCs are assumed to have in order to overcome the higher costs they face in foreign markets (Hymer, 1976; Dunning, 1993). These arise as the foreign firm is unfamiliar with the market, demand characteristics, supplier links and so on that are known to the domestic firm. These firm-specific assets are often of a technological nature – more than 80% of royalty payments for international technology transfers were made by affiliates to their parent companies (UNCTAD, 1997). They also have public-good characteristics: excluding other (in this case local) firms from obtaining the knowledge can be difficult. The evidence for a productivity differential between foreign and domestic firms in favour of MNCs appears to be convincing (cf. Griffith and Simpson, 2002 and Girma et al., 2001). However, the empirical evidence as to the actual extent of spillovers from MNCs is rather mixed as the reviews by Blomström and Kokko (1998) and Görg and Greenaway (2001) show. Our brief review of the literature puts the accent on the methodologies used, with the view of positioning this paper.

Several studies of technology spillovers via FDI have explored the hypothesis that the incidence of externalities is dependent on absorptive capacity (Cohen and Levinthal, 1989) of local firms or plants. Depending upon data availability and the context of the investigation, two basic approaches are usually adopted. One is to divide the plants in the sample according to some perceived proxies for absorptive capacity, and compare the degrees of spillovers across the sub-samples. Thus Kokko et al. (1996) divide their sample of Uruguayan manufacturing plants by the size of their technology gap vis-à-vis foreign owned firms, and find that spillovers are present when the technology gaps are 'moderate'. Girma and Wakelin (2001) stratify micro data for the UK electronics industry according to size and skill intensity, and report that smaller plants or plants in the lower distribution of skill intensity lack the necessary absorptive capacity to benefit from FDI in their sector. But they also report that large establishments with higher skill intensity do not benefit from FDI, as they presumably operate near the technological frontier. This last point is echoed in the work of Haskel *et al.* (2002), where all industries in the same UK micro data set are pooled and the sample split by employment, TFP and skill intensity quartiles. But in contrast to Girma and Wakelin (2001), they find that plants further away from the technology frontier gain most from foreign presence in their sector. This seems to point to the conclusion that low absorptive capacity is not a hindrance to learning from foreign technology.

Econometric estimators that are generated from such exogenous sample splitting procedures can run into serious inference problems though. Hansen (2000) demonstrates that standard asymptotic confidence intervals need not be valid. There is also the obvious criticism that the sample tends to be divided in an ad hoc fashion as the decision concerning the appropriate thresholds at which to split it is made somewhat arbitrarily. Furthermore, plants within the same group are constrained to have the same absorptive capacity, a tenuous assumption in view of the substantial heterogeneity exhibited across plants.

The second approach is to *linearly* interact a proxy for absorptive capacity with the FDI variable of choice. Such a proxy can be R&D intensity (Kinoshita, 2001) or initial level of technology gap from the frontier (Girma *et al.*, 2001; Griffith *et al., 2002*). The first two confirm that the parameter capturing the degree of spillovers increases in the measure of absorptive capacity, whereas Griffith *et al. (2002*) report that establishments that are further behind the technology frontier experience higher catch-up rates. A limitation of this modelling strategy is that the linear interaction term places the a priori restriction that spillovers are monotonically increasing (or decreasing) with absorptive capacity. But it may be the case that a certain level of R&D intensity is needed before firms benefit from FDI-generated externalities. Or conversely, firms above a certain level of initial technology may not, at the margin, gain much from multinational activity in their sector. This suggests the need for a more flexible specification that can accommodate different spillover-absorptive capacity configurations.

Empirical work has also focused on whether the ability to learn from foreign presence is retarded by geographical distance. Several reasons are advanced as to why productivity spillovers may be geographically bounded. First, direct contacts with local suppliers and distributors may be local to minimise transport costs and facilitate communication between the supplier/distributor and the MNC. Second, it known that the training of employees by MNCs and subsequent labour turnover one of the main technology transmission mechanisms (Fosfuri et al., 2001). But since regional labour mobility is extremely low (e.g., Greenaway *et al.*, 2002), many of the benefits of a better skilled workforce with tacit technical knowledge gained from MNCs will be experienced by local employers. Third, demonstration effects may also be local if firms only closely observe and imitate other firms in the same region (Blomström and Kokko, 1996). Theory from the economic geography literature predicts that, if knowledge is tacit and uncodified, it is transmitted more effectively over small distances. Jaffe *et al.* (1996) and Verspagen and Schoenmakers (2001) underline the significance of maintaining face-to-face contacts in the process of technological learning. Audretsch and Feldman (1996) maintain that the cost of transmitting knowledge rises with spatial distance.

In the international technology diffusion literature (see Keller, 2000), the effect of geographical proximity is measured by physical distance (a continuous variable) between countries. By contrast, the FDI literature relies on the differential effects of MNC activity within regions of the same country, and employs discrete measures of localisation. This usually takes the form of dichotomising the total amount of FDI into that taking place in the firm's region, and that occurring outside it. Further distinction is sometimes made between FDI in the *same sector and region* and a more general FDI at the regional level. For example, the work of Harris and Robinson (2001) and Haskel *et al.* (2002) consider FDI at regional levels as a whole[1]. This captures general agglomeration effects rather than intra-industry spillovers, and both authors fail to establish any beneficial effect from total FDI activity in the region.

[1] Harris and Robinson (2001) use local authorities to measure the extent of local FDI.

By contrast Girma and Wakelin (2001) employ two measures of sectoral FDI: that taking place in the firms region and outside the region. They find that intra-industry spillovers are mostly confined to the region in which the MNC locates, and interpret this as indicating that being geographically close to foreign firms matters. This accords with Driffield (1999) who examines the role of productivity spillovers from inward investment in the UK using sector-level data, and reports that there are positive productivity spillovers from FDI in the same sector and region[2]. The case for localised intra-industry spillovers from FDI into the U.K[3] is further strengthened by Griffith et al. (2002)'s finding of a faster catch-up by domestic establishments to the technological frontier within the region.

As mentioned in the introduction, our study also makes an attempt at testing the conjecture that the nature of the externalities from FDI depends on its motivation to locate in the host region (Cantwell and Narula, 2001). Traditionally FDI has chiefly been characterised as being motivated by the MNC's desire to exploit its firm-specific assets abroad (Hymer, 1976). Recently, another general motive for undertaking FDI appears to be identified: acquisition of technological knowledge residing in the host country or technology sourcing. Fosfuri and Motta (1999) label such MNCs 'multinationals without advantages' and argue that knowledge gained by locating close to market leaders can then easily be transferred to all subsidiaries of the multinational firm. Wesson (1999) presents a game theoretic model in which a firm may undertake FDI in order to secure access to certain types of valuable assets. But he also shows that asset-seeking and asset-exploiting motivations are not mutually exclusive.

The existence of technology sourcing FDI is empirically established by Kogut and Chang (1991) and Neven and Siotis (1996), among others. However, to the best of our knowledge, the paper by Driffield and Love (2001) is the only one that tests if the spillovers implications of technology sourcing FDI are different from those of technology exploiting FDI. Using industry-aggregated FDI flows to the U.K, Driffield and Love (2001) conclude that technology sourcing FDI has detrimental effects on the domestic sector's productivity trajectory.

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[2] Driffield (1999) also finds that FDI in the sector but outside the region has a negative impact on productivity, presumably due to increased competition.

[3] In the context of developing countries, Sjöholm (1998) indicates that FDI to Indonesia benefits domestic establishments in neighbouring industries within the region, and Aitken and Harrison (1999) fail find any significant impact of region and sector-specific FDI on domestic firms' productivity.

3. The threshold model

If absorptive capacity mediates the pattern of FDI-induced TFP growth, this implies that the spillovers regression functions are not identical across all domestic firms. Without a prior knowledge as to how the coefficients on the FDI variables vary with absorptive capacity, the problem is best addressed by using endogenous threshold regression techniques developed by Hansen (2000), rather than arbitrarily assuming cut-off values . The main problem at the heart of threshold regression is this: since the threshold or cut-off value is unknown, it has to be estimated, which means that standard econometric theory of estimation and inference is not valid. The seminal contribution of Hansen (2000) is to provide a distribution theory that allows one to make valid statistical inference on threshold models.

Our estimating equation is

$$\Delta TFP_{it} = \beta' X_{it-1} + \gamma_1 FDI_{ijt-1} I(ABC_{it-1} \leq \alpha) + \gamma_2 FDI_{ijt-1} I(ABC_{it-1} > \alpha) + \varepsilon_{it} \quad (1)$$

where I(.) is the indicator function; i, j and t index firms, four-digit industries and time periods respectively. On the other hand, X is a vector of variables hypothesised to impact on firms TFP[4] growth trajectories, and it consists of TFP_{t-1}, age, export intensity. FDI is a vector that consists of two variables capturing four-digit industry foreign presence in the firm's region and outside the region. The random error ε satisfies the conditional moment restrictions $E(\varepsilon_{it} \mid X_{it-1}, FDI_{ijt-1}, ABC_{it-1}) = 0$, where ABC denotes absorptive capacity which is defined as:

$$ABC_{it} = \frac{TFP_{it-1}}{\max\limits_{industry}(TFP_{sjt-1})} \quad (2)$$

A high level of absorptive capacity is supposed to indicate technological congruity with industry leaders, which are predominantly foreign firms in the data.

Equation (1) divides the FDI parameter (hence the observations) into two regimes depending on whether absorptive capacity is smaller or larger than the threshold level α. Four estimation issues need to be addressed: (i) how to jointly estimate the threshold value α and the slope parameters β, γ_1 and γ_2; (ii) how to test the hypothesis $H_0 : \gamma_1 = \gamma_2$; (iii)

[4] TFP is expressed in logs

how to construct confidence intervals for α ; and finally (iv) how to obtain the asymptotic distribution of the slope parameters. We discuss each in turn.

Let $S_n(\beta,\gamma(\alpha))$ represent the sum of squared errors for equation (1), where n is sample size, and the dependence of the γ parameters on the threshold value α is denoted in an obvious way. Because of this dependence, S(.) is not linear in the parameters but rather a step function ,with steps occurring at some distinct values of the threshold variable ABC. But conditional on a threshold value, say α_0, S(.) is linear in β and γ so that it can be minimised to yield the conditional OLS[5] estimators $\hat{\beta}(\alpha_0)$ and $\hat{\gamma}(\alpha_0)$. Now denote the resulting so-called concentrated sum of squared errors function by $S(\alpha_0)$. If one experiments with all possible values of absorptive capacity, the estimator of the threshold corresponds to the value of α that yields the smallest sum of squared errors. That is:

$$\hat{\alpha} = \arg\min_{\alpha} S(\alpha). \tag{3}$$

In this paper this minimisation problem is solved by a grid search over the 393 absorptive capacity quantiles {1.00%, 1.25%, 1.50%, … , 98.75%, 99%}. Once the sample-splitting value of α is identified, the estimates of the slope parameters are readily available.
The next problem is to determine whether the threshold or absorptive capacity effect in (1) is significant. The hypothesis of no absorptive capacity effect can be written as

$$H_0 : \gamma_1 = \gamma_2 \tag{4}$$

The testing of this linear constraint is not as trivial as it may seem. Since the threshold variable is not identified under the null hypothesis of no threshold effect, classical tests such as the Lagrange Multiplier (LM) test, do not have standard distributions. This means that critical values cannot be read off standard χ^2 distribution tables, for example. But the critical values of the test statistics can be approximated using bootstrapping techniques[6]. We follow Hansen (2000) and bootstrap[7] the p-value for the

[5] As shown by Caner and Hansen (2001), the basic procedure applies to more complicated minimands such as GMM criterion functions.
[6] In an earlier paper that explores the general problem of hypothesis testing when a nuisance parameter is not identified under the null, Hansen (1996) shows that bootstrapping generates asymptotically correct p-values.
[7] Professor Bruce Hansen provides Gauss codes for implementing the threshold models at his homepage http://www.ssc.wisc.edu/~bhansen/

heteroscedasticity-consistent LM tests. The bootstrap dependent variable is generated from the distribution $N(0,\hat{\varepsilon}^2)$ by *fixing* the regressors. Here $\hat{\varepsilon}$ is the residual from the estimated threshold model (1).

If a threshold effect is found (i.e. $\gamma_1 \neq \gamma_2$), it is important to form a confidence interval of the critical absorptive capacity level. It is not enough to simply say, for example, that firms below the 25th percentile have less learning capabilities without attaching a degree of certainty with it. Thus one needs to test for the particular threshold value as

$$H_o : \alpha = \alpha_0 \tag{5}$$

It should be noted that this is not equivalent to testing the null hypothesis in (4). Under normality, the likelihood ratio test statistic $LR_n(\alpha) = n\dfrac{S_n(\alpha) - S_n(\hat{\alpha})}{S_n(\hat{\alpha})}$ is routinely used in standard econometric applications to test for particular parametric values. But Hansen (2000) proves that $LR_n(\alpha)$ does not have a standard χ^2 distribution under the endogenous sample-splitting scheme. He then derives the correct distribution function and tabulates the appropriate asymptotic critical values[8].

The final ingredient in this estimation strategy is to establish the asymptotic distribution of the slope coefficients. Although these parameters depend on the estimated threshold value $\hat{\alpha}$, Hansen (2000) argues that this dependence is not of first-order asymptotic importance. Consequently the usual distribution theory (i.e. asymptotically normal) can be applied to the estimated slope coefficients. We finish this section by noting that if a threshold effect is identified, a second or higher order threshold model can be further estimated by extending the methodology described in this section in a straightforward fashion.

4 Database construction, sample characteristics and TFP measurement

The primary source of information is the *OneSource* database of private and public companies, which is derived from the accounts that companies are legally required to deposit at Companies House[9]. All public limited companies, all companies with employees greater than 50, and the top companies based on turnover, net worth, total assets, or shareholders funds (whichever is largest) up to a maximum of 110,000 companies are

[8] See his Table I on page 582 . Hansen (2000) also shows how LR(α) can be scaled by some estimable constant to make it robust to heteroscedasticity.

included in the database. Companies that are dissolved or in the process of liquidation are excluded.

This database has a number of attractions as a sample frame for investigating the relationship between productivity spillovers, absorptive capacity and geographic proximity. First, information on employment, physical capital, output and cost of goods sold, which is crucial for the generation of productivity indicators, are provided in a consistent way both across firms and across time. It is constantly updated, making it more relevant for policy analysis. Second, *OneSource* is one the very few databases with firm level export data. Third *OneSource* gives the geographical location of the companies and information on a company's main activity, which is a five-digit industry indicator.

For our empirical analysis we divide firms into fourteen regions, and construct the degree of foreign penetration at four-digit industry level for each region. Foreign penetration is defined as the proportion of employment accounted for by MNCs[10]. Clearly the choice of a 'region' is always fairly arbitrary. We have chosen this division partly for reasons of tractability, but also because it corresponds to areas with definite regional identities[11]. A distance-weighted measure of foreign presence outside the region but within the same sector is also computed, following the literature on neighbourhood agglomeration (Adsera, 2000). For a firm in region *r* and industry *s* this is defined as $OUTFDI_{rs} = \sum_{k \neq r} \frac{FDI_{ks}}{d_{kr}^2}$, where d_{kr} is the distance (in miles) between the largest cities in regions *k* and *r*. Table 1 gives the list of the regions and charts the development of FDI during the period of analysis. It is apparent that foreign presence has almost doubled in almost all regions.

We basically work with subsidiaries of domestic companies and independent domestic producers that do not own any subsidiaries[12]. The top and bottom one percentile firms in terms of employment, labour productivity and capital intensity were omitted to mitigate the possible impact of outliers. Firms with annual employment or output growth exceeding

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[9] For this study we used the *OneSource* CD-ROM entitled "UK companies, Vol. 1", for October 2000.
[10] We relied on some information from the British Census of Production published by the Office of National Statistics to gross-up aggregate industry employment from *OneSource*, as the latter does not have a comprehensive coverage.
[11] Northern Ireland is not included in our database.

100% were also omitted, given doubts about the reliability of these extreme data points. Our final sample contains information on 7516 companies over the period 1989 to 1999, yielding a total of 48527 observations. Half of the firms in the sample have observations for at least seven years. To allow cross-time comparisons we converted current to constant price values using highly disaggregated output and input price deflators[13]. Although the use of firm level prices is the ideal way of constructing real values, such data is not available and these five-digit price indices help to ameliorate problems associated with more aggregate price deflators. Table 2 provides summary statistics of some variable of interest. It can be seen that there is considerable variation in the variables, particularly between firms. The overall average export intensity in the sample is 8.93%, but less than half of the firms has ever exported. Among exporters average export intensity is 24.2%.

Whatever the object of the productivity analysis, it is very important to obtain consistent estimates of the parameters of the production function. Using log values, we write the production function as $y_{it} \equiv f(l_{it}, m_{it}, k_{it}, r_{it}, TFP_{it})$, where y is output and TFP is a firm and time-varying productivity shock. There are four factors of production: labour (l), material or cost of goods sold (m) and capital (k) which is measured by the book value of fixed assets, and intangible assets (r). The intangible assets variable in *OneSource* is an estimate of the firms' investment in R&D and marketing, and the value of patents and copyrights and goodwill. Braunerhjelm (1996) argues that it is a variable that more closely corresponds to the theoretical notion of 'firm specific assets'.

For estimation purposes we employ a first-order Taylor approximation and write the production function as:

$$y_{it} = \beta_0 + \beta_s l_{it} + \beta_m m_{it} + \beta_k k_{it} + \beta_r r_{it} + TFP_{it} \qquad 6)$$

TFP is assumed to follow the following AR(1) process:

$$TFP_{it} = \rho TFP_{it-1} + \delta D_t + f_i + v_{it} \qquad (7)$$

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[12] UK-owned parent companies were omitted if they have consolidated accounts as this leads to double counting.

[13] Five-digit SIC92 level price indices are obtained from the Office for National Statistics, but some extrapolation is done for missing years/sectors.

where D is a common year-specific shock, *f* is a time-invariant firm-specific and *v* a random error term which includes the effects of observable[14] as well as unobservable ones. Notice that we do not simply model productivity as a fixed effect, that would imply that TFP differences are fixed, and there is no role for technology diffusion (convergence). We estimate equation (6) for each the 100 three-digit[15] SIC92 industries available in our sample, including subsidiaries of foreign firms to facilitate the computation of relative technology gap from the frontier. To reflect that MNCs may use different technology, they are allowed to have distinct factor elasticity parameters.

Recently the fundamental assumption of pooling individual times series data has been questioned. Pesaran and Smith (1995) demonstrate that standard GMM estimators of dynamic panel models lead to invalid inference if the response parameters are characterised by heterogeneity. They argue that one is better off averaging parameters from individual time series regressions. This is not feasible here since the individual firm's time series data is not of adequate length (75% of them have no more than 9 observations). However, we take some comfort from a recent comparative study by Baltagi and Griffin (1997) which concludes that efficiency gains from pooling are likely to more than offset the biases due to individual heterogeneity. Baltagi and Griffin (1997) especially point out the desirable properties of the GLS-AR(1) estimator, and we use this to obtain estimates of the factor elasticities, and derive TFP as a residual term. Naturally we experimented with other TFP measurement approaches, but generally find that they are highly correlated.

We relied on the work of Driffield and Love (2001) to dichotomise the manufacturing industry in our sample into sectors that have received *predominantly* technology sourcing FDI (TSFDI) and technology exploiting FDI (TSFDI). FDI is deemed to be technology sourcing if the R&D intensity in the sector is greater than sectoral R&D intensity in the countries the FDI is coming from. This exercise indicates that TSFDI is concentrated in the following sectors: mechanical and instrument engineering; vehicles, textiles, leather and clothing; paper, printing and publishing; and rubber and plastic. These are found to span 51 five-digit industries, and contain more than a quarter of the sample observations. As reported in Table 3, TSFDI industries enjoy higher productivity and pay more to their

[14] It is to be recalled that our main TFP growth model given in equation (1) takes into account some of these factors.

workers, but employment is lower by 8% on average[16]. Finally Table 3 also shows significant employment, wages and productivity premia due to exporting. It has been extensively documented in the literature that exporting firms are bigger and more productive, and pay higher wages to their workers (cf. Bernard and Jensen, 1999; Girma et al., 2001). This is also borne out by the data used in this study.

5. Major Findings

Separate analysis is conducted for the four sub-samples comprising our data set, viz. exporting or non-exporting firms in sectors where FDI is deemed to be either technology sourcing (TSFDI) or technology exploiting (TEFDI).

Before estimating the endogenous threshold model of productivity spillovers described in equation (1), we experimented with two specifications that assume the relationship between absorptive capacity and externalities from FDI is either linear or quadratic. Thus we postulates that the spillovers parameters can be written as

$$\gamma = d_0 + d_1 ABC + d_2 ABC^2 \tag{8}$$

where the d's are parameters to be estimated. Setting $d_2 = 0$ gives the linear model, which implies that the degree of spillovers either increases or decreases with absorptive capacity monotonically. The quadratic specification is more flexible in that it allows for the *rate* at which productivity grows to vary with absorptive capacity. For example with $d_1 > 0$ and $d_2 < 0$, the initially positive impact of FDI on productivity will start to diminish once absorptive capacity gets past the critical level $ABC = -\frac{d_1}{2d_2}$. The econometric estimates from the linear and quadratic models are presented in Tables 4 and 5.

In all sub-samples and specifications, the estimated coefficient of initial TFP is negative. This is consistent with the notion of β-convergence where low productivity firms grow faster than high productivity ones. Firms in sectors with technology sourcing FDI are uniformly found to have faster convergence rates. These catch-up rates, which denote the

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[15] Estimation of production functions is not performed at the more disaggregated 232 four-digit level to maximise the number of observations available for estimation.

[16] Using data from Annual Respondents Database (ARD) for 1986 and 1988 provided by the Office for National Statistics in the UK, we find that the proportion of computer employees in domestic firms in TSFDI

speed at which a firm approaches its steady level of TFP ranges from 9% to 15%. Thus, assuming that the firm at the technology frontier is in its steady state, the typical domestic firm will need between 4.6 and 7.7 years to cover half of the technology gap. Conditional on initial TFP, older firms grow at a slower rate, but the magnitude of the point estimates suggests that the between-ages difference might not be practically important. The results also suggest that the share of exports in total shipments exerts a growth-enhancing influence.

Focusing on the role played by the four-digit level FDI variables, it is apparent that productivity spillovers due to MNCs show remarkable heterogeneity, depending on where the FDI is located, and whether it is technology sourcing or exploiting and the degree of absorptive capacity. The linear interaction model presented in Table 4 predicts that technology spillovers from *regional* FDI is uniformly positive, and increases with absorptive capacity in sectors with technology exploiting multinationals (TEFDI). It is also clear this beneficial effect is significantly more pronounced for exporting firms, suggesting that for a given level of technological capability, exporters have more learning potential than their non-exporting counterparts. The externalities from TEFDI outside the region are not as spectacular, and are mainly confined to exporting firms. But again more absorptive capacity seems to be the key to benefiting from FDI. At the average exporting firm absorptive capacity level of 23.75%, a 10% increases of extra-regional FDI leads productivity to grow by 1.6 percentage points[17]. So the implied magnitude of the spillovers is not economically insignificant.

The contrast with the pattern of spillovers from technology sourcing multinationals (TSFDI) is stark. There is no discernible positive externality, either regional or extra-regional, for exporters. Furthermore non-exporters appear to lose out from the presence of TSFDI in their region, probably reflecting competition effects. However, this detrimental impact is somewhat tempered as the absorptive capacity of the firms increases.

The estimates from the model which quadratically interacts the FDI variables with absorptive capacity reveals that the linear model might be missing some important non-

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sectors is not statistically different from their foreign counterparts. This suggests that the R&D based dichotomisation of sectors made by Driffield and Love (2001) might be reasonably accurate.

[17] All calculations of marginal effects are based on significant coefficients only.

linearities in the spillovers-learning capability linkage. As reported in Table 5, an *inverted* U-shaped relationship emerges between absorptive capacity and the degree of spillovers from regional TEFDI. For exporters, FDI-induced productivity growth starts to decline once the absorptive capacity reaches the critical level of 22.6%, which is close to the average value. On the other hand, the last column of Table 5 indicates a U-shaped relationship between absorptive capacity and spillovers from extra-regional TSFDI for non-exporters. The initial negative effects become positive as absorptive capacity turns past the 56% mark. However only 5% of the firms in the relevant sub-sample satisfy this condition, so that most of the firms lose out from foreign presence in their sector. Although the quadratic specification appears to be more informative than the linear one, it still suffers from the shortcoming that the shape of the absorptive capacity-spillovers linkage is determined a priori to have at most one turning point. Furthermore interpreting confidence intervals for the turning points, if any, is not that easy as the standard errors of the parameters differ from one data point to another[18].

We now turn our attention to the discussion of the estimates from the endogenous threshold model. The first step was to determine the number of thresholds by estimating model (1) allowing for zero, one two and more thresholds on the two FDI variables. We sequentially tested the null hypothesis in (4) and Lagrange Multiplier (and Likelihood Ratio) test statistics and their bootstrapped[19] p-values are given in Table 6. Apart from the sample of exporters in TSFDI industries, we found the existence of either single or double threshold values. The point estimates of the thresholds and the corresponding 95% confidence intervals are reported in Table 7. The intervals for the first thresholds are reasonably tight, especially for the TEFDI sector where they fall within four or five percentage points of the point estimates. A graphical way to find this confidence interval for the threshold estimates is to plot the likelihood ratio sequence in α, $LR(\alpha)$, against α and draw a flat line at the critical value. The segment of the curve that lies below the flat line will be the 'no-rejection' region, that is, the confidence interval of the threshold estimate. Figure 1 illustrates how the confidence interval for the first threshold in the sample of non-exporters in TSFDI sectors is obtained, using the 95% critical value of 7.35.

[18] In quadratic models standard errors are usually computed at the mean value of the regressors , using the so-called 'delta method'.

[19] The p-values are based on 1000 bootstrap replications.

Table 8 gives the percentage of firms that fall in a particular class of absorptive capacity. The overwhelming majority of exporting firms in TEFDI reside between the absorptive capacity values of 8.6% and 64.3%, and it is this class of exporters that benefit most from foreign presence in their sector. The first column of Table 9 shows that a 10% percent increase in regional and extra-regional sectoral FDI boosts their productivity growth by 2.74 and 1.89 percentage points respectively. This is quite a significant amount and the benefit is quite widespread, it affects between 75% and 92% of the firms. Notice that productivity growth of these firms is more responsive to regional FDI compared to FDI taking place outside their region, pointing to the importance of localisation of spillovers. But nonetheless we establish strong evidence that exporting does indeed help surmount the constraint of geographical distance in technology transfer from FDI. This is perhaps not surprising as successful exporters are those able to overcome the cost of entry associated with cross-border trade, including the cost of gathering information on foreign markets and technology. Data permitting, it would be interesting to conduct a detailed analysis to identify the exact channels through which exporting raises absorptive capacity.

Exporters in the upper end of the absorptive capacity quantiles do not benefit from FDI in any way. This is perhaps indicative of the fact that domestic firms that are near the technology frontier do not have much to learn from foreign firms. But these firms account for no more than 5.1% of exporters in the population. At the other end of the spectrum, there is weak evidence that the 4.8% to 19.2% of firms at the lower end of absorptive capacity quantiles loose out from foreign presence, presumably because of competitive pressures, although it is not possible to isolate the real reason behind this negative externality.

The productivity spillovers due to TEFDI in the sample of non-exporters follow the same pattern, but exhibit a lower intensity. For example, as can be seen from the second column of Table 9, a 10 % increase in extra-regional FDI would only generate a one percentage point growth in the TFP. But the most remarkable difference is that FDI-induced benefits seem to be enjoyed by 45%-60% of non-exporters only, emphasising the importance of exporting as a channel of enhancing absorptive capacity.

The picture that emerges from the TSFDI is totally different. Multinational enterprises seeking to source superior British technology do not seem to exert any discernible influence on the productivity growth trajectories of indigenous exporters. But the results for the sample of non-exporters are mixed. Up to 61.6% of the firms at the lower end of the productivity distribution actually lose out from foreign presence *outside* their region. As the last column of Table 9 reveals, the magnitude of this loss is not trivial: TFP would grow by less than 2.7 percentage points following a 10% increase in extra-regional FDI, than would otherwise have been the case. The threshold regression estimates also show a very modest gain from regional TSFDI that accrues to the remaining non-exporters. But overall the results seem to confirm that if FDI is motivated by home technological advantage, productivity spillovers due to foreign presence tend to be non-existent (cf. Driffield and Love, 2001). Needless to say more work is needed before reaching a firmer conclusion regarding the relative merits of (apparent) technology-sourcing multinationals.

6. Conclusion

This paper provides fresh econometric evidence on the influence of geographic proximity and absorptive capacity in technology transfer from FDI. We investigate the issue using firm level data for one of the most important hosts to FDI, the UK. We also apply a recently developed and more powerful methodology than previous work. As a result, the threshold model we employed was able to quantify the significance of absorptive capacity rather than assume it. Overall, substantial heterogeneity in the way FDI-induced externalities are distributed across domestic firms was uncovered, with the key findings being the presence of threshold effects in the spillovers-absorptive capacity nexus, and the fact that productivity gains due to MNCs are largely geographically bounded. The additional findings that the learning potential of exporters is less constrained by geographic space, and externalities generated from predominantly technology-sourcing multinationals are negligible suggest interesting topics for future research.

Figure 1 : 95% confidence interval for threshold:
Non-exporters in TSFDI sectors

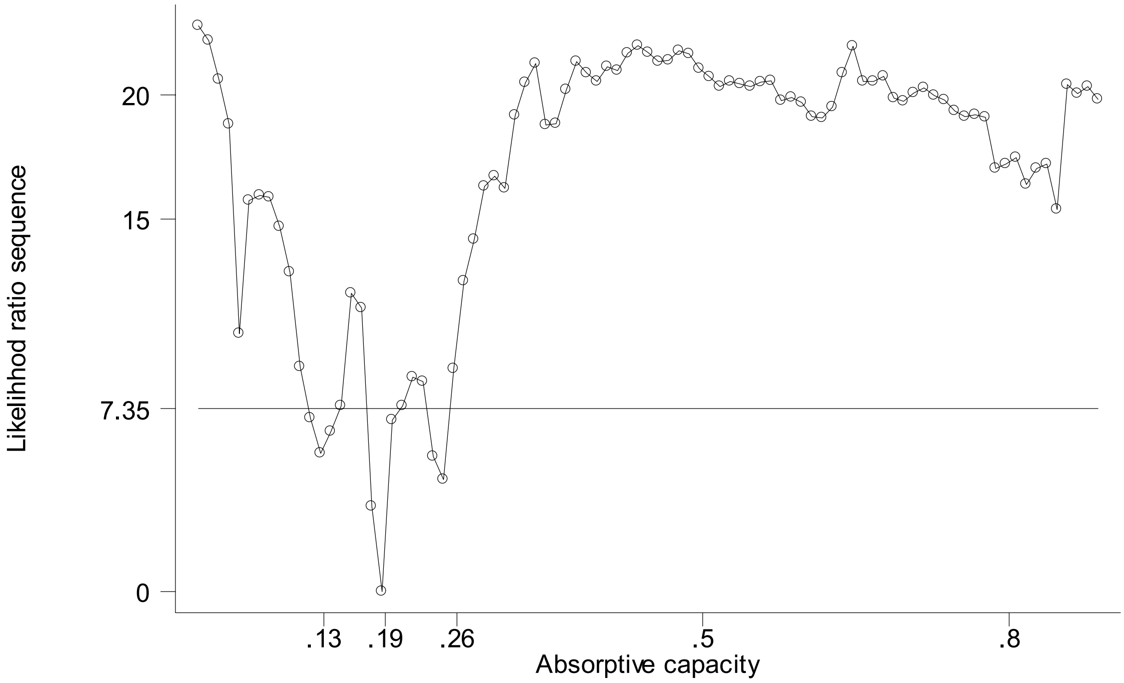

Table 1:

Development of Regional FDI : 1989-1999

Region	**FDI in region**		**Distance-weighted FDI outside region**	
	1989	1999	1989	1999
Central London	9.21%	12.12%	5.58%	12.66%
Central South	6.56%	13.56%	6.38%	13.04%
East Anglia	8.69%	12.31%	6.52%	12.28%
East Midlands	6.03%	13.90%	5.84%	12.00%
Home Counties	10.24%	19.86%	6.99%	14.29%
North East	6.09%	11.79%	5.61%	10.67%
North Scotland	8.64%	16.89%	5.11%	11.86%
North West	7.29%	14.54%	5.59%	11.15%
Outer London	9.55%	19.58%	6.45%	13.25%
South East	8.37%	19.01%	6.26%	12.73%
South West	6.45%	13.80%	5.28%	12.20%
South Scotland	9.24%	15.44%	5.90%	11.61%
Wales	9.21%	17.62%	6.52%	13.12%
West Midlands	4.97%	11.65%	5.71%	12.57%

Note: FDI is measured by the share of employment in foreign firms.

Table 2
Summary statistics

Variable		Mean	Std. Dev.
Employment	Overall	183.39	332.44
	Between		334.51
	Within		79.02
Output*	Overall	13586.27	36579.74
	Between		39362.47
	Within		8012.44
Capital intensity *	Overall	1546.68	2247.44
	Between		2611.52
	Within		933.398
Labour productivity*	Overall	76.84	54.97
	Between		56.75
	Within		19.68
Export intensity	Overall	0.089	0.19
	Between		0.17
	Within		0.07
No. of firms	7471		
No. of observation	47951		

Note:
(i) Variables with * are expressed in £ '000

Table 3
Percentage premia to exporting firms and technology sourcing (TSFDI) sectors

	Employment	Labour Productivity	TFP	Wages
TSFDI	-7.95**	2.32**	1.1*	4.66**
Exporters	22.12**	5.95**	8.29**	2.61**
Observations	47951	47951	47951	47951

Notes:
(i) Results are based on OLS regressions with robust standard errors
(ii) * significant at 5%; ** significant at 1%

Table 4
FDI spillovers and absorptive capacity:
Linear interaction model

	Technology exploiting FDI		**Technology sourcing FDI**	
TFP Growth	Exporters	Non exporters	Exporters	Non exporters
Initial TFP	-0.0923	-0.0859	-0.1464	-0.1269
	(18.03)**	(23.33)**	(13.52)**	(11.95)**
Age	-0.0002	-0.0004	-0.0003	-0.0005
	(2.85)**	(6.89)**	(2.30)*	(3.53)**
Export intensity	0.0206	0.0000	0.0400	0.0000
	(2.18)*	(.)	(3.26)**	(.)
FDI in region	0.0189	0.0047	0.0014	-0.1168
	(2.84)**	(0.25)	(0.04)	(3.50)**
FDI in region * GAP	0.0796	0.0125	0.0773	0.5596
	(2.06)*	(2.18)*	(0.53)	(4.58)**
FDI outside region	-0.0387	-0.0523	-0.0454	0.0211
	(0.95)	(1.40)	(0.66)	(0.30)
FDI outside region * GAP	0.0714	0.2081	0.4182	-0.2629
	(2.48)*	(1.56)	(1.43)	(1.06)
Mean absorptive capacity	23.75%	21.1%	24.4%	23.97%
Observations	10726	18883	4948	5203

Notes:
(i) Robust t-statistics in parentheses
(ii) significant at 5%; ** significant at 1%
(iii) Throughout the paper FDI is expressed in logs.

Table 5
FDI spillovers and absorptive capacity:
Quadratic interaction model

	Technology exploiting FDI		**Technology sourcing FDI**	
TFP Growth	Exporters	Non exporters	Exporters	Non exporters
Initial TFP	-0.0926	-0.0859	-0.1478	-0.1290
	(18.03)**	(23.33)**	(13.32)**	(11.80)**
Age	-0.0002	-0.0004	-0.0003	-0.0005
	(2.80)**	(6.89)**	(2.35)*	(3.50)**
Export intensity	0.0215	0.0000	0.0405	0.0000
	(2.27)*	(.)	(3.31)**	(.)
FDI in region	0.0247	0.0050	0.0301	-0.1040
	(1.64)	(2.25)*	(0.76)	(2.86)**
FDI in region * GAP	0.0144	0.0171	-0.4238	0.3058
	(2.09)*	(2.11)*	(1.78)	(1.07)
FDI in region * GAP squared	-0.0319	-0.0519	0.9425	0.5266
	(2.30)*	(2.03)*	(1.64)	(0.94)
FDI outside region	-0.0004	-0.0201	-0.0623	0.0575
	(2.01)*	(0.46)	(0.90)	(0.78)
FDI outside region * GAP	0.4633	-0.1507	0.7652	-0.6723
	(2.47)*	(0.50)	(1.49)	(2.40)*
FDI outside region * GAP squared	-0.5810	0.5604	-0.6902	0.6019
	(2.22)*	(1.13)	(0.73)	(1.68)*
Mean absorptive capacity	23.75%	21.1%	24.4%	23.97%
Observations	10726	18883	4948	5203

Notes
(i) Robust t-statistics in parentheses
(ii) significant at 5%; ** significant at 1%

Table 6
Tests for threshold effects on FDI variables:
P-values from Likelihood Ratio (LR) and Lagrange Multiplier tests

	Technology exploiting FDI Exporters	Non-exporters	Technology sourcing FDI Exporters	Non-exporters
Single threshold	**LM .007** **LR .005**	**LM .004** **LR .001**	LM .666 LR .534	**LM .048** **P-value .037**
Double threshold	**LM .015** **LR .022**	**LM .023** **LR .017**		LM .896 LR .713
Triple threshold	LM .354 LR .272	LM .549 LR .491		

Note:
(i) Emboldened cells show statistically significant thresholds.

Table 7
Tests estimates [and 95% confidence intervals

	Technology exploiting FDI Exporters	Non-exporters	Technology sourcing FDI Exporters	Non-exporters
First threshold	$\hat{\alpha}_1$: 8.6% [5.5%, 13%]	$\hat{\alpha}_1$: 15.1% [12.5%, 17.5%]		$\hat{\alpha}_1$: 18.9 % [13 %, 26 %]
Second threshold	$\hat{\alpha}_2$: 64.3% [58.5%, 75%]	$\hat{\alpha}_2$: 66.6% [59%, 78%]		

Notes:
(i) The threshold estimates refer to the level of absorptive capacity.
(ii) Confidence intervals in threshold models need not be symmetric.

Table 8
Proportion of firms in each absorptive capacity regime

Absorptive capacity class	**Technology exploiting FDI** **Exporters**	**non exporters**	**Technology Sourcing FDI**
ABC <= $\hat{\alpha}_1$	[4.8% 19.2%]	[39.8% 50.1%]	[40.0% 61.6%]
$\hat{\alpha}_1$ < ABC<=$\hat{\alpha}_2$	[75.7% 91.9%]	[45.3% 57.9%]	
ABC > $\hat{\alpha}_2$	[3.3% 5.1%]	[2.3% 4.6%]	

Note:
(i) The calculations are based on the point estimates and the upper or lower bounds of the 95% intervals of the threshold estimates given in Table 7.

Table 9
FDI spillovers and absorptive capacity:
Threshold regression estimates

	Technology exploiting FDI		**Technology sourcing FDI**		
TFP Growth	Exporters	Non exporters	Exporters		Non exporters
Initial TFP	-0.0881	-0.0819	-0.1326		-0.1242
	(18.52)**	(21.93)**	(14.97)**		(11.83)**
Age	-0.0002	-0.0004	-0.0003		-0.0005
	(2.84)**	(6.93)**	(2.43)*		(3.42)**
Export intensity	0.0205	0.0000	0.0409		0.0000
	(2.17)*	(.)	(3.35)**		(.)
FDI in region			0.0259		
$I(AC< \hat{\alpha}_1)$	-0.019	0.0293	(0.83)	$I(AC < \hat{\alpha}_1)$	0.0417
	(1.99)*	(0.35)			(0.85)
$I(\hat{\alpha}_1 <= AC < \hat{\alpha}_2)$	0.0274	0.0211		$I(AC>\hat{\alpha}_1)$	0.007
	(3.42)**	(2.03)**			(2.43)*
$I(AC > \hat{\alpha}_2)$	0.014	0.008			
	(0.89)	(1.97)*			
FDI outside region			0.0357		
$I(AC< \hat{\alpha}_1)$	0.1735	0.0374	(0.60)	$I(AC < \hat{\alpha}_1)$	-0.0267
	(1.05)	(0.80)			(2.58)*
$I(\hat{\alpha}_1 <= AC < \hat{\alpha}_2)$	0.0186	0.010		$I(AC>\hat{\alpha}_2)$	0.0678
	(2.33)*	(2.56)*			(1.09)
$I(AC > \hat{\alpha}_2)$	-0.0020	0.0329			
	(0.01)	(0.76)			
Observations	10726	18883	4948		5203

Note
(i) Robust t-statistics in parentheses
(ii) significant at 5%; ** significant at 1%

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