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

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I. 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 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 absorptive capacity on 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 spillover from multinationals. Initially FDI-induced productivity gains increase at an increasing rate, but the rate diminishes as the absorptive capacity of domestic firms increase. 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. 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 III we present the threshold model, and outline the estimation strategy. Section IV gives a description of the basic characteristics of the data. The main empirical findings are presented in Section V. The last section concludes.

II. 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 surveys by Blomström and Kokko (1998) and Görg and Greenaway (2001) show. The following 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 is 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.*, 2001a and 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 is known that the training of employees by MNCs and subsequent labour turnover is 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), it is likely that the benefits of MNCs will be mostly 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) underline the significance of maintaining face-to-face contacts in the process of technological learning, and Audretsch and Feldman (1996) argue 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 (2002) and Haskel *et al.* (2002) consider FDI at regional level as a whole[1]. This captures general agglomeration effects rather than intra-industry spillovers, and both papers fail to establish any beneficial effect from total FDI activity in the region.

[1] Harris and Robinson (2002) 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, pointing to the conclusion that being geographically close to foreign firms matters. This accords with Driffield (2000) 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 for locating 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

[2] Driffield (2000) also finds that FDI in the sector but outside the region has a negative impact on productivity, presumably due to increased competition.

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.

III. The endogenous 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 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 (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

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

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. It consists of initial *TFP* , absorptive capacity (see below for exact definition), age, firm level export intensity (defined as the share of exports in total

[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 to find any significant impact of region and sector-specific FDI on domestic firms' productivity.

sales), four-digit industry imports penetration[5] to capture potential efficiency-enhancing effects of international product market competition (e.g. Levinsohn, 1993) and a Herfindhal index of four-digit industry concentration. It is expected that firms in industries with higher market concentration would experience lower TFP growth (e.g. Nickell 1996).

In equation (1) FDI is a vector that consists of two variables capturing four-digit industry foreign presence in the firm's region and outside the region[6]. The random error ε satisfies the conditional moment restrictions $E(e_{it} \mid X_{it-1}, FDI_{ijt-1}, ABC_{it-1}) = 0$, where ABC denotes absorptive capacity which is defined as:

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

A high level of absorptive capacity is supposed to indicate technological congruity with industry leaders, which are predominantly foreign firms in the data[7].

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 $H_0 : g_1 = g_2$; (iii) 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.

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[4] TFP is expressed in logs
[5] Imports penetration is defined as imports divided by domestic output + imports – exports.
[6] To account for the fact that the pattern of FDI across regions and sectors might to some extent be dictated by the productivity dynamics of indigenous firms we allow for sectoral dummies in the spillovers equations. Moreover, the dichotomisation of FDI into technology-sourcing and technology-exploiting ones will go some way into mitigating concern about FDI endogeneity.
[7] The use of the maximum (econometrically estimated) TFP at the industry level as the denominator in the construction of our absorptive capacity variable is of course susceptible to the problem of outliers. When the maximum TFP exceeds the median industry TFP by more than 3 standard deviations, we used the next highest value as the industry frontier. However it is worth noting that the relative position of the firm within the industry is invariant to the choice of denominator, and hence it does not impact on the threshold estimation

Let $S_n(\boldsymbol{b},\boldsymbol{g}(\boldsymbol{a}))$ represent the sum of squared errors for equation (1), where n is the 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 $\boldsymbol{a}_0$, S(.) is linear in β and γ so that it can be minimised to yield the conditional OLS[8] estimators $\hat{\boldsymbol{b}}(\boldsymbol{a}_0)$ and $\hat{g}(\boldsymbol{a}_0)$. Now denote the resulting so-called concentrated sum of squared errors function by $S(\boldsymbol{a}_0)$. 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:

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

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

$$H_0 : \boldsymbol{g}_1 = \boldsymbol{g}_2 \tag{4}$$

The testing of this linear constraint is not as trivial as it may seem. Since the threshold parameter α 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.

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strategy. See Griffith et al (2002, page 16) for a similar argument that correctly identifying the exact position of the technology frontier is not crucial from the point of view of econometric estimation.

[8] As shown by Caner and Hansen (2001), the basic procedure applies to more complicated minimands such as GMM criterion functions.

Accordingly we follow Hansen (2000) and bootstrap[9] the p-value for the heteroscedasticity-consistent LM tests. In what follows we briefly describe this bootstrap procedure.

By estimating the model under the restriction imposed by equation (4), one can of course compute the *actual* LM test statistic. But the asymptotic distribution of this statistic is non-standard as it depends on the moments of the sample (Hansen, 1996). Consequently, critical values cannot be read off standard $\boldsymbol{c}^2$ distribution tables. Instead p-values are constructed from the bootstrap by treating the regressors (X and FDI) and the threshold variable (ABC) in equation (1) as given, and holding their values fixed in each bootstrap sample. The bootstrap dependent variable is then generated under the null by drawing with replacement a sample of errors from $N(0,\hat{\boldsymbol{e}}^2)$, where $\hat{\boldsymbol{e}}$ is the residual from the estimated threshold model (1). Once we have the bootstrap sample, we estimate the model under the null hypothesis and compute the *simulated* LM statistic. This procedure is repeated a large number of times[10], and the bootstrap estimate of the p-value under the null is given by the percentage of bootstraps for which the simulated statistic exceeds the actual one. As Hansen (1996) shows, this procedure provides asymptotically correct p-values.

If a threshold effect is found (i.e. $\boldsymbol{g}_1 \neq \boldsymbol{g}_2$), 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 to it. Thus one needs to test for the particular threshold value as

$$H_o : \boldsymbol{a} = \boldsymbol{a}_0 \tag{5}$$

It should be noted that this is not equivalent to testing the null hypothesis in (4). Under normality, the likelihood ratio test statistic $LR_n(\boldsymbol{a}) = n\frac{S_n(\boldsymbol{a}) - S_n(\hat{\boldsymbol{a}})}{S_n(\hat{\boldsymbol{a}})}$ is routinely used in

[9] Professor Bruce Hansen provides Gauss codes for implementing the threshold models at his homepage http://www.ssc.wisc.edu/~bhansen/

[10] In this paper we perform 1000 bootstrap replications.

standard econometric applications to test for particular parametric values. But Hansen (2000) proves that $LR_n(\boldsymbol{a})$ does not have a standard $\boldsymbol{c}^2$ distribution under the endogenous sample-splitting scheme. He then derives the correct distribution function and tabulates the appropriate asymptotic critical values[11].

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 $\hat{a}$, Hansen (2000) demonstrates 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. 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.

In addition to estimating the endogenous threshold model of productivity spillovers, we also experiment with two specifications that assume that the relationship between absorptive capacity and externalities from FDI is either linear or quadratic. Thus we postulates that the spillovers parameter (i.e. the coefficient on the FDI variable in equation 1) can be written as

$$g = d_0 + d_1 ABC + d_2 ABC^2 \tag{6}$$

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

[11] 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 heteroskedasticity.

absorptive capacity gets past the critical level $\delta = -\frac{d_1}{2d_2}$. The asymptotic variance of this turning point can be constructed via the 'delta' method, given consistent estimates of d_1 and d_2 ($\hat{d}_1$ and $\hat{d}_2$, say). Kuha and Temple (2003) have worked out the exact expression for this variance, and it can be expressed as

$$Var(\hat{\delta}) = \frac{1}{4\hat{d}_2^2}\left[\mathrm{var}(\hat{d}_1) + 4\hat{\delta}\,\mathrm{cov}(\hat{d}_1, \hat{d}_2) + 4\hat{\delta}^2\,\mathrm{var}(\hat{d}_2)\right] \tag{7}$$

IV. Database construction and sample characteristics

As discussed in the previous section the aim of this paper is to investigate the role of absorptive capacity in mediating productivity spillovers from FDI to domestic establishments. Clearly a micro level data set with ownership indicators is best suited for this purpose. The primary source of information used in this paper 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[12]. All public limited companies, all companies with more than 50 employees, 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 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

[12] For this study we used the *OneSource* CD-ROM entitled "UK companies, Vol. 1", for October 2000.

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. However *OneSource* gives foreign-ownership status for the latest year alone, so that it is not easy to exactly identify when a firm became a subsidiary of a foreign multinational. To track the dynamics of ownership, we matched the population of manufacturing firms in *OneSource*, to the list of U.K. firms acquired by foreign multinationals obtained from the ONS[13]. The imports data are derived from the OECD trade statistics CD-ROM, and an industry-product concordance file provided by the Office for National Statistics is used to aggregate imports to four-digit SIC92 industry level[14].

For our empirical analysis we divide firms into fourteen regions, and construct the degree of foreign direct investment (FDI) at four-digit industry level for each region. FDI is defined as the proportion of employment accounted for by MNCs[15]. 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[16]. 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.

[13] This required considerable effort, and I wish to thank Mehtap Hisarciklilar for helping me in the matching process.
[14] I acknowledge the assistance of Mauro Pisu in this regard.
[15] 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.
[16] Northern Ireland is not included in the database.

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.

We basically work with subsidiaries of domestic companies and independent domestic producers that do not own any subsidiaries[17]. 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 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, and to allow cross-time comparisons we converted current to constant price values using highly disaggregated output and input price deflators[18]. Although the use of firm level prices is the ideal way of constructing real values, such data are not available and these five-digit price indices help to ameliorate problems associated with more aggregate price deflators.

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

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

Table 2 provides summary statistics of some variable of interest, and it can be seen that there is considerable variation in the variables, particularly between firms. The overall sample average export intensity is 8.9%, but less than half of the firms have ever exported. Among exporters average export intensity is 24.2%.

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: Variables with * are expressed in £ '000

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), 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 the following four-input Cobb-Douglas production function:

$$y_{it} = \beta_0 + \beta_s l_{it} + \beta_m m_{it} + \beta_k k_{it} + \beta_r r_{it} + TFP_{it} \tag{8}$$

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

$$TFP_{it} = \rho TFP_{it-1} + \delta D_t + f_i + v_{it} \tag{9}$$

where D represents time dummies to capture common macro shocks, f is a time-invariant firm-specific effect and v a random error term which includes the effects of observable[19] 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 thus no role for technology diffusion (convergence). We estimate equation (8) for each of the 100 three-digit[20] 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

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

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 workers, but employment is lower by 8% on average[21].

Table 3 also shows significant employment, wages and productivity premia due to exporting. For example exporters are on average 8.29% more productive than non-exporters. 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., 2001b). This is also borne out by the data used in this study. But it is worth noting that the results reported in Table 3 only show that exporting and performance are correlated. As such they do not necessarily imply causality from exporting to performance.

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

[21] Using data from the 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 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.

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 heteroskedasticity and within-firm serial correlation robust standard errors
(ii) * significant at 5%; ** significant at 1%

The empirical findings of substantial heterogeneity in firm performance across exporters and non-exporters have spun off a number of recent theoretical papers attempting to explain this firm level heterogeneity in a formal setting. Examples of such models are Melitz (2003) and Bernard et al. (2003), both of which allow for firm level heterogeneity in efficiency and find that in equilibrium more efficient firms select into exporting, while less efficient ones serve the local market only. In light of this self-selection into export markets, it would be wrong to automatically conclude that exporting enhances absorptive capacity. However, on the basis of propensity-score matched firms from the same sample used in this paper, Girma et al (2001b) show that although U.K firms self-select into exporting, their productivity further improves after entering the international market.

V. Major Findings

Separate analysis is conducted for two sub-samples comprising firms in sectors where FDI is deemed to be either technology sourcing (TSFDI) or technology exploiting (TEFDI). To gauge the importance of allowing for the motivation of FDI, we also estimate our models using the whole sample. The results from the linear, quadratic and endogenous threshold models are discussed in turn.

V.1 The linear model

The econometric estimates from the linear interaction model are presented in Tables 4.

Table 4
FDI spillovers and absorptive capacity:
Linear interaction model

	All sectors		**Technology sourcing FDI sectors**		**Technology exploiting FDI sectors**	
	Without industry dummies	With industry dummies	Without industry dummies	With industry dummies	Without industry dummies	With industry dummies
Initial TFP	-0.1127	-0.1254	-0.1621	-0.1831	-0.1013	-0.1120
	(25.11)**	(24.09)**	(14.97)**	(14.33)**	(20.64)**	(19.98)**
Absorptive capacity	-0.1984	-0.2554	-0.2829	-0.3489	-0.1759	-0.2250
	(11.69)**	(12.57)**	(5.56)**	(6.27)**	(9.58)**	(10.31)**
Age	-0.0003	-0.0002	-0.0002	-0.0001	-0.0002	-0.0002
	(2.03)*	(2.51)*	(2.17)*	(2.42)*	(1.99)*	(2.19)*
Export intensity	0.0730	0.0734	0.1299	0.1300	0.0363	0.0369
	(3.40)**	(3.42)**	(3.65)**	(3.67)**	(2.37)**	(2.40)**
FDI in region	0.0129	0.0132	0.0993	0.1003	0.0334	0.0234
	(2.62)**	(2.83)**	(0.80)	(0.80)	(2.21)**	(2.23)**
FDI in region * ABC	-0.0240	-0.0223	0.0919	-0.0809	0.0244	0.0251
	(0.35)	(0.33)	(1.57)	(0.50)	(2.34)**	(2.35)**
FDI outside region	-0.2363	-0.1993	-0.0277	-0.0900	0.0013	0.00104
	(2.30)*	(1.97)*	(2.75)**	(0.31)	(2.18)*	(2.90)*
FDI outside region * ABC	0.2811	0.2855	0.3088	0.2830	0.1643	0.1804
	(2.05)*	(2.10)*	(2.83)**	(0.22)	(2.15)*	(2.22)**
Imports competition	0.0110	0.0084	0.0235	0.0044	0.0087	0.0058
	(2.87)**	(2.07)*	(2.97)*	(0.35)	(2.10)*	(0.32)
Industry concentration	-0.0043	0.0027	-0.0206	-0.0043	-0.0090	-0.0030
	(2.45)**	(0.25)	(2.60)**	(0.11)	(2.87)**	(0.26)
Mean absorptive capacity	67.36%	67.36%	65.78%	65.78%	70.12%	70.12%
Observations	32374	32374	8330	8330	24044	24044

Notes:
(i) Heteroskedasticity and within-firm serial correlation robust t-statistics are given in parentheses.
(ii) significant at 5%; ** significant at 1%
(iii) In all regressions FDI is expressed in logs. To be more precise we used log (1 + FDI) to deal with zero values.

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. Also firms with lower absorptive capacity (or larger technology gap) are found to experience faster rates of productivity growth. This is in line with the result reported in Griffith et al (2002). 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 and the degree of international product market competition (i.e. imports intensity) exert a growth-enhancing influence. By contrast, market concentration is found to have an adverse effect on productivity growth, consistent with the finding of Nickell (1996). However, the effects of industry level import competition and domestic concentration become statistically insignificant when industry-specific fixed effects are included in the model.

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. The linear interaction model predicts that technology spillovers from *regional* FDI is uniformly positive, and increases with absorptive capacity in sectors with technology exploiting multinationals (TEFDI). The externalities from TEFDI outside the region are less pronounced, but once again more absorptive capacity seems to be the key to benefiting from FDI.

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. In fact firms appear to have lost out from the presence of TSFDI in their region, presumably reflecting 'market stealing' effects by multinationals. However, this detrimental impact diminishes as absorptive capacity increases, and it disappears altogether when industry-specific effects are included.

When all sectors are pooled together, the econometric estimates suggest that an increase in FDI within the region is associated with modest productivity growth, irrespective of the absorptive capacity of the domestic establishments. This reinforces the idea that taking account of heterogeneity in response to FDI matters at the firm level.

V.2 The quadratic model

The estimates from the model that quadratically interacts the FDI variables with absorptive capacity reveal that the linear model might be missing some important non-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. In the model with industry dummies, FDI-induced productivity growth starts to decline once the absorptive capacity reaches the critical level of 68.2%, and the 95% asymptotic confidence interval for this turning point is found to be (56.9%, 79.5%). There is also an inverted-U shaped relationship between absorptive capacity and spillovers from extra-regional TSFDI. The rate of technology transfer from multinational firms located outside the domestic firm's region starts to decrease as absorptive capacity turns past the 46.5% mark. The asymptotic confidence interval for this turning point is calculated to be (30.7%, 62.3%). Furthermore, consistent with the linear interaction model, no discernible FDI-induced productivity effects are found in sector where technology-sourcing multinationals are prevalent. This confirms the conclusion of Driffield and Love (2001).

Table 5
FDI spillovers and absorptive capacity:
Quadratic interaction model

	All sectors		**Technology sourcing FDI sectors**		**Technology exploiting FDI sectors**	
	Without industry dummies	With industry dummies	Without industry dummies	With industry dummies	Without industry dummies	With industry dummies
Initial TFP	-0.1202	-0.1382	-0.1782	-0.2196	-0.1080	-0.1217
	(25.54)**	(24.50)**	(16.36)**	(16.67)**	(20.69)**	(19.99)**
ABC	-0.2159	-0.2919	-0.3383	-0.4718	-0.1916	-0.2518
	(12.26)**	(13.56)**	(6.49)**	(7.97)**	(10.06)**	(10.98)**
Age	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001
	(2.09)*	(2.68)**	(2.04)*	(2.44)**	(1.97)*	(2.34)*
Export intensity	0.0725	0.0727	0.1286	0.1279	0.0362	0.0369
	(3.38)**	(3.40)**	(3.65)**	(3.67)**	(1.37)	(1.40)
FDI in region	0.0256	0.0267	0.0261	0.019	0.0118	0.0103
	(1.90)	(1.93)	(1.12)	(1.36)	(2.74)**	(2.73)**
FDI in region * ABC	0.0117	0.0137	0.0297	0.0219	0.0119	0.012
	(2.76)**	(2.75)**	(0.70)	(0.59)	(2.98)**	(3.10)**
FDI in region * ABC squared	-0.0510	-0.0545	-0.0250	-0.0214	-0.0094	-0.0088
	(2.97)**	(2.63)**	(1268)	(1.16)	(2.83)**	(2.88)**
FDI outside region	-0.0155	-0.0133	-0.0800	-0.0871	-0.3064	-0.3957
	(5.07)**	(5.44)**	(0.85)	(1.58)	(3.51)**	(3.70)**
FDI outside region * ABC	0.0350	0.03034	0.025	0.023	0.6069	0.7807
	(5.30)**	(6.02)**	(0.51)	(0.47)	(3.83)**	(4.27)**
FDI outside region * ABC squared	-0.025	-0.0199	-0.0069	-0.0077	-0.9676	-0.8384
	(5.27)**	(6.09)**	(0.53)	(0.72)	(3.88)**	(4.35)**
Imports competition	0.0115	0.0088	0.0315	0.0048	0.0088	0.0059
	(2.98)**	(2.15)*	(2.55)*	(2.38)*	(2.12)*	(2.36)*
Industry concentration	-0.0039	-0.0029	-0.0292	-0.0009	-0.0108	-0.0033
	(2.40)*	(0.26)	(2.84)	(0.02)	(2.05)*	(0.28)
Observations	32374	32374	8330	8330	24044	24044

Notes:
(i) Heteroskedasticity and within-firm serial correlation robust t-statistics are given in parentheses.
(ii) significant at 5%; ** significant at 1%

V.3 The endogenous threshold model

Although the quadratic specification appears to be more informative than the linear model, 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. We now turn our attention to the discussion of the estimates from the endogenous threshold model, which is a more flexible estimation strategy.

The first step was to determine the number of thresholds by estimating model (1) allowing for zero, one, two and more absorptive capacity thresholds on the two FDI variables. Recall that the threshold is defined in terms of absorptive capacity that is based on TFP estimates from a four-input Cobb-Douglas production function estimates across 100 industries. The effects of FDI on TFP are not estimated jointly with the parameters of the production function because we first need to obtain a measure of initial TFP so as to rank firms according to their absorptive capacity.

We sequentially tested the null hypothesis in (4) using LM test statistics and their bootstrapped p-values, and the results from this exercise are summarised in Table 6.

Table 6
Tests for threshold effects:
p-values from LM tests

	All sectors	**Technology sourcing FDI**	**Technology exploiting FDI**
Single threshold	.007**	.034*	.009**
Double threshold	.012**	.323	.016**
Triple threshold	.222		.319

Notes:

(i) The values reported in the above table are based on the model with industry dummies. Further results are available from the author upon request.

(ii) significant at 5%; ** significant at 1%

When all sectors are pooled together or in sectors with technology- exploiting FDI, we find the existence of two threshold values, but in sectors with technology sourcing FDI only a single threshold is identified. The point estimates of the thresholds and the corresponding 95% confidence intervals are reported in Table 7.

Table 7
Threshold estimates [and 95% confidence intervals]

	All sectors	**Technology sourcing FDI**	**Technology exploiting FDI**
First threshold	$\hat{a}_1$: 48.7% [41.3%, 56.1%]	$\hat{a}_1$: 51.2 % [43.5 %, 66.2 %]	$\hat{a}_1$: 41.5% [37.2%, 46.7%]
Second threshold	$\hat{a}_2$: 72.6% [63.5%, 79.5%]		$\hat{a}_2$: 76.6% [71.7%, 80.8%]

Notes:
(i) The threshold estimates refer to the level of absorptive capacity.
(ii) Confidence intervals in threshold models need not be symmetric.
(iii) The confidence intervals reported are based on the model with industry dummies. Further results are available from the author upon request.

The confidence intervals for the first thresholds are reasonably tight, especially for the TEFDI sectors where the lower and upper bounds of the confidence interval fall within four or five percentage points of the point estimate.

A graphical way to find confidence intervals for the threshold estimates is to plot the likelihood ratio sequence in α, LR(α), 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 that pools all sectors is obtained, using the 95% critical value of 7.35.

Figure 1: 95% confidence interval for the first threshold:

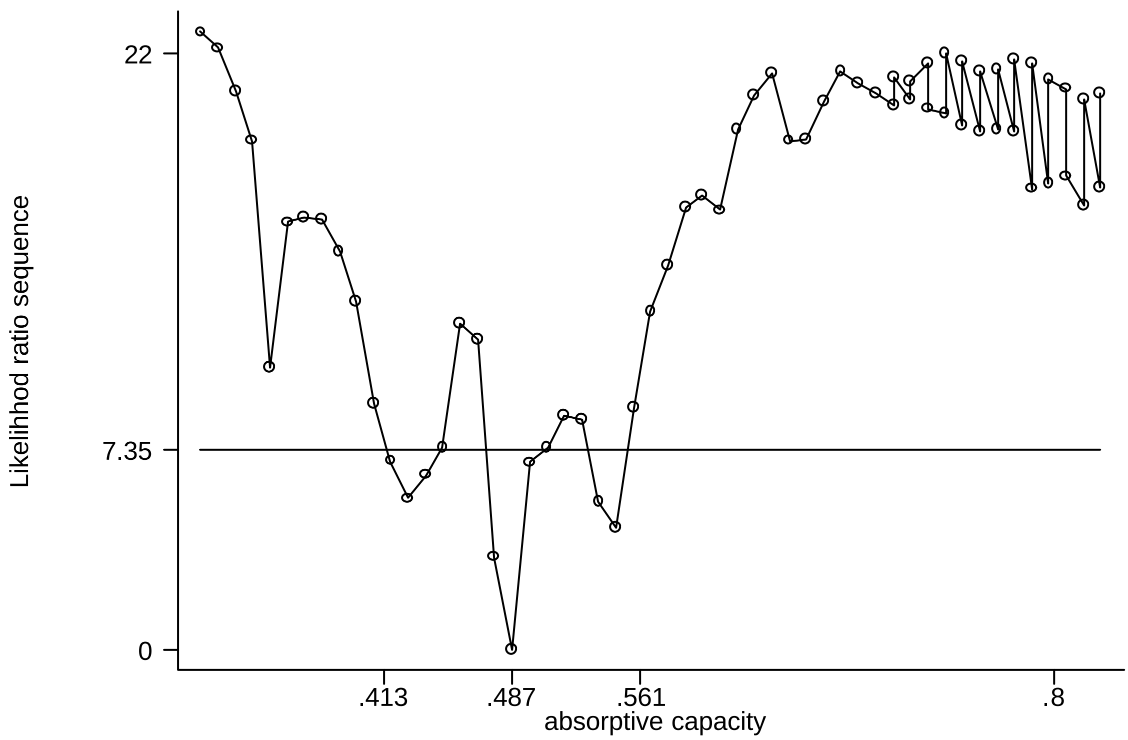

Table 8 gives the percentage of firms that fall in a particular class of absorptive capacity. Note that those are not confidence intervals per se, but they are based on the upper or lower bounds of the 95% intervals of the threshold estimates given in Table 7. For example according to Table 7 the 95% confidence interval for the first (absorptive capacity) threshold in the pooled sample lies between 41.3% and 56.1%. From the data we find that that 17.3% of the firms have absorptive capacity less than the lower bound of 41.3%, and 23.9% of the firms have absorptive capacity less than the upper bound value (i.e. 56.1%).

Table 8
Proportion of firms in each absorptive capacity regime

Absorptive capacity class	**All sectors**	**Technology Sourcing FDI**	**Technology exploiting FDI**
ABC <= $\hat{a}_1$	[17.3% 23.9%]	[19.8% 30.1%]	[9.3% 15.0%]
$\hat{a}_1$ < ABC<= $\hat{a}_2$	[68.8% 83.4%]		[75.3% 87.9%]
ABC > $\hat{a}_2$	[6.5% 8.2%]		[8.3% 9.6%]

The overwhelming majority of firms in TEFDI resides between the two critical values of absorptive capacity ($\hat{a}_1$ and $\hat{a}_2$), and as reported in Table 9 it is this class of domestic firms that benefit most from foreign presence. A doubling of regional and extra-regional sectoral FDI boosts their productivity growth by 2.66 and 1.43 percentage points respectively in the short run, and the corresponding long run effects are 21.55 and 11.58 percentage points. Notice that indigenous firms' productivity growth is more responsive to regional FDI compared to FDI taking place outside their region, pointing to the importance of localisation of spillovers.

Table 9
FDI spillovers and absorptive capacity:
Threshold regression estimates

	All sectors		**Technology sourcing FDI sectors**		**Technology exploiting FDI sectors**	
	Without industry dummies	With industry dummies	Without industry dummies	With industry dummies	Without industry dummies	With industry dummies
Initial TFP	-0.1212	-0.1403	-0.1784	-0.2220	-0.1090	-0.1235
	(25.55)**	(24.40)**	(15.93)**	(16.28)**	(20.76)**	(19.93)**
ABC	-0.2189	-0.2991	-0.3379	-0.4790	-0.1946	-0.2578
	(12.51)**	(13.85)**	(6.37)**	(7.96)**	(10.28)**	(11.18)**
Age	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001
	(2.09)*	(2.72)**	(1.04)	(1.48)	(2.09)*	(2.37)*
Export intensity	0.0726	0.0729	0.1285	0.1278	0.0363	0.0371
	(3.39)**	(3.41)**	(3.65)**	(3.67)**	(1.38)	(1.41)
FDI in region						
I(ABC< $\hat{a}_1$)	-0.016	-0.014	-0.026	-0.024	-0.007	-0.004
	(2.12)*	(2.07)*	(3.042)**	(2.07)*	(2.33)*	(1.17)
I($\hat{a}_1$<=ABC< $\hat{a}_2$)	0.011	0.099			0.0297	0.0266
	(2.61)**	(2.17)**			(2.79)**	(2.86)**
I(ABC > $\hat{a}_2$)	0.015	0.009	0.007	0.010	0.015	0.010
	(1.67)*	(1.12)	(0.81)	(0.21)	(1.57)	(0.13)
FDI outside region						
I(ABC< $\hat{a}_1$)	-0.006	-0.032	-0.015	-0.011	0.011	-0.021
	(1.35)	(0.99)	(2.56)*	(1.98)*	(0.15)	(0.56)
I($\hat{a}_1$<=ABC< $\hat{a}_2$)	0.010	0.009			0.0196	0.0143
	(2.19)*	(2.03)*			(2.46)*	(2.17)*
I(ABC > $\hat{a}_2$)	0.007	0.001	0.004	0.002	0.011	0.008
	(0.93)	(0.67)	(0.45)	(0.07)	(1.49)	(0.91)

Imports competition	0.0115	0.0087	0.0319	0.0051	0.0086	0.0058
	(2.96)**	(2.14)*	(2.58)**	(0.40)	(2.09)*	(2.33)*
Industry concentration	-0.0035	-0.0028	-0.0292	-0.0002	-0.0106	0.0030
	(2.36)*	(0.25)	(2.83)**	(0.01)	(2.03)*	(1.26)
$\hat{a}_1$	47.9%	48.7%	50.8%	51.2%	41.0%	41.5%
$\hat{a}_2$	71.8%	72.6%	50.8%	51.2%	76.2%	76.6%
Observations	32374	32374	8330	8330	24044	24044

Notes
(i) Heteroskedasticity and within-firm serial correlation robust t-statistics are given in parentheses
(ii) significant at 5%; ** significant at 1%
(iii) $\hat{a}_1$ and $\hat{a}_2$ are the same in the TSDFI sectors as only a single threshold was identified.

By contrast firms in the upper end of the absorptive capacity quantiles (that is with ABC > $\hat{a}_2$) do not appear to benefit from FDI. 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 9.6 % of firms in the sample. There is also weak evidence that firms at the lower end of absorptive capacity quantiles (with ABC < $\hat{a}_1$), have experienced negative externalities from foreign presence. However, these negative effects become insignificant when industry dummies are included.

In line with the linear and quadratic models, the picture that emerges from the TSFDI sample is totally different. Multinational enterprises seeking to source superior British technology do not seem to exert any discernible positive influence on the productivity growth trajectories of indigenous establishments. In fact up to 30.1% of the firms at the lower end of the productivity distribution have actually lost out from foreign presence inside and outside their region. As the relevant estimates in the fifth column of Table 9 indicate, the magnitude of this loss is not trivial: a doubling of regional FDI would be associated with a short run and long run decrease of TFP by 2.4 and 10.8 percentage points respectively. This negative externality from FDI is likely to be due to a decline in market share because of competitive pressure, and the resultant lower capacity utilisation: as output declines, average cost will go up causing productivity to decrease. Overall the results from the threshold model based on the TSFDI sample seem to confirm that if the location decision of multinationals is motivated by home technological advantages, positive productivity spillovers due to foreign presence tend to be non-existent. Needless to say more work is needed before reaching a firmer conclusion regarding the relative merits of (apparent) technology-sourcing multinationals.

VI. Conclusion

This paper provides fresh microeconometric evidence on the influence of absorptive capacity in technology transfer from FDI for one of the most important hosts to multinational companies, the UK. Overall, substantial heterogeneity in the way FDI-induced externalities are distributed across domestic firms was uncovered, with the key results being: (i) the presence of non-linear threshold effects in the spillovers-absorptive capacity nexus; (ii) the fact that productivity gains due to multinational companies are more pronounced in the case of regional FDI, and (iii) the robust finding that externalities generated from predominantly technology-sourcing multinationals are negligible.

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