

No.1 / July 2003

Foreign direct investment, spillovers and absorptive capacity: Evidence from quantile regressions

Sourafel Girma
University of Leicester

Holger Görg
University of Nottingham and IZA Bonn



IIS Discussion Paper No. 01

Foreign direct investment, spillovers and absorptive capacity: Evidence from quantile regressions

Sourafel Girma

Holger Görg

Disclaimer

Any opinions expressed here are those of the author(s) and not those of the IIS.
All works posted here are owned and copyrighted by the author(s).
Papers may only be downloaded for personal use only.

Foreign direct investment, spillovers and absorptive capacity: Evidence from quantile regressions

Sourafel Girma
University of Leicester

Holger Görg*
University of Nottingham and IZA Bonn

Abstract

This paper focuses on the role of absorptive capacity in determining whether or not domestic firms benefit from productivity spillovers from FDI using establishment level data for the UK. We distinguish the effect of FDI in the same sector and region from FDI in the same sector but outside the region. We also allow for different effects of FDI on establishments located at different quantiles of the productivity distribution by using conditional quantile regression. Overall, while there is substantial heterogeneity in results across sectors and quantiles, our findings clearly suggest that both absorptive capacity and distance matter for productivity spillover benefits. We find evidence for a u-shaped relationship between absorptive capacity and productivity spillovers from FDI in the region, while there is an inverted u-shaped relationship for spillovers from FDI outside the region. We also analyse in some detail the impact of changes in absorptive capacity on establishments' ability to benefit from spillovers.

Keywords: foreign direct investment, absorptive capacity, productivity spillovers, quantile regressions

JEL classification: F21, F23

* Address for correspondence: Holger Görg, School of Economics, University of Nottingham, Nottingham NG7 2RD, UK. Tel. +44 115 846 6393, fax +44 115 951 4159, email holger.gorg@nottingham.ac.uk.

The authors are grateful to the ONS Business Data Linking Project for providing access to the ARD database. Thanks are due to David Greenaway, Steve Redding, Beata Smarzynska, Eric Strobl and participants at the RES conference in Warwick, a NUPI/TIK workshop in Oslo and a seminar at IIS Dublin for helpful comments on an earlier draft. Financial support from the European Commission Fifth Framework Programme (Grant No. HPSE-CT-1999-00017) and the Leverhulme Trust (Grant No. F114/BF) is gratefully acknowledged.

Foreign direct investment, spillovers and absorptive capacity: Evidence from quantile regressions

1 Introduction

Many governments around the globe actively attempt to attract multinational companies (MNCs) to locate in their country using substantial fiscal and financial incentives. For example, Head (1998) reports that the government of Alabama paid the equivalent of \$150,000 per employee to Mercedes for locating its new plant in the state in 1994. Across the Atlantic, the British Government provided an estimated \$30,000 and \$50,000 per employee to attract Samsung and Siemens respectively to the North East of England in the late 1990s (Girma et al., 2001). Some countries also provide tax incentives. For example, Ireland offers a corporate tax rate of 10 percent to all manufacturing firms locating in the country.

One of the main rationales for these policy interventions is the belief that domestic firms can benefit from the presence of foreign multinationals through productivity spillovers. Hence, domestic firms may improve their productivity if there are positive externalities emanating from multinationals, although domestic firms may be affected adversely if competition with multinationals reduces output for domestic firms and, thus, leads to reductions in productivity (see Aitken and Harrison, 1999).

Recent surveys of the literature conclude that there does not appear to be much evidence that there are aggregate benefits which accrue to all types of domestic firms equally (see Görg and Greenaway, 2002 and Blomström and Kokko, 1998). Rather, it appears that conditions in the host country seem crucial for whether or not there are positive spillovers. In particular, the absorptive capacity of domestic firms, that is their

ability to utilise spillovers from multinationals to improve their productivity, has been found to be an important determinant for whether or not domestic firms benefit from foreign direct investment (FDI).¹

The aim of this paper is to focus in detail on the role of establishments' absorptive capacity in determining the magnitude of possible benefits from FDI. To this end we calculate absorptive capacity as the gap in total factor productivity (TFP) between the domestic establishment and the "industry leader" and allow for a non-linear relationship between FDI and absorptive capacity. We then investigate how changes in absorptive capacity may determine the benefits to domestic firms from productivity spillovers. We also take account of a geographical dimension to spillovers by calculating two groups of variables to proxy spillovers from FDI located within the region and outside the region. This reflects the idea put forward by, for example, Audretsch (1998) who argues that geographical proximity is necessary to facilitate knowledge spillovers as "knowledge is vague, difficult to codify, and often only serendipitously recognized" (p. 21).

A further contribution of our paper is that we allow for different effects of FDI on TFP at different quantiles of the productivity distribution. While standard least squares estimates the mean of the dependent variable conditional on the covariates we use the quantile regression estimator to estimate the effect of the covariates on different quantiles of the productivity distribution. This allows us to take better account of the large and persistent heterogeneity in productivity dynamics across establishments.²

¹ Keller (2001) also discusses the role of absorptive capacity for successful technology diffusion.

² There has been only one previous application of quantile regression in the literature on productivity spillovers. Dimelis and Louri (2002) use this technique to analyse spillovers from FDI for a sample of Greek manufacturing firms. However, they only have cross-sectional data available which does not allow them to control properly for time invariant effects on productivity that may be correlated with foreign presence (see Görg and Strobl, 2001). Furthermore, they only analyse the effect of FDI on domestic labour productivity while we look at total factor productivity.

We present a detailed analysis of the role of absorptive capacity for FDI spillovers (both within and outside the region) using data for the UK.³ Our results indicate that both absorptive capacity and geographical distance are important in determining whether or not domestic establishments benefit from FDI spillovers. We find a u-shape relationship between absorptive capacity and spillovers from FDI in the region, and an inverted u-shape relationship outside the region. We determine the exact turning points for both quadratic relationships and evaluate the marginal effects of changes in absorptive capacity on productivity holding the FDI variables constant.

The remainder of the paper is structured as follows. Section 2 presents a brief review of the literature on the role of absorptive capacity for FDI spillovers. Section 3 outlines the econometric methodology and discusses the advantages of using quantile regression in the context of our paper. Section 4 discusses the dataset and some summary statistics while Section 5 presents the empirical results. Finally, Section 6 concludes.

2 The role of absorptive capacity

In an early theoretical paper, Findlay (1978) emphasised the importance of relative backwardness for the speed of adoption of new technologies and spillover benefits from multinationals. Findlay's model suggests that the greater the technological distance between the (less advanced) host and (advanced) home country, the greater the available opportunities to exploit in the former and the more rapidly new technology is adopted. Hence, the potential for positive spillovers is higher the larger the technology gap between host and home. More recently, however, this view has changed. For

³ While much of the literature on productivity spillovers has focused on developing countries, the literature on developed countries has grown substantially in the very recent past. In particular, there have been a

example, Glass and Saggi (1998) also see a role for technological distance between the host and home country, however, they see the technology gap as indicating absorptive capacity of host country firms, i.e., their ability to absorb and utilise the knowledge that spills over from multinationals. The larger the gap, the less likely are host country firms to have the human capital and technological know-how to benefit from the technology transferred by the multinationals and, hence, the lower is the potential for spillover benefits.

There have been a number of empirical studies examining this issue. Kokko (1994) advances the idea that spillovers depend on the complexity of the technology transferred by multinationals, and the technology gap (that is, the difference in labour productivity) between domestic firms and MNCs. Using cross-section industry level data for Mexico he finds no evidence for spillovers in industries where multinationals use highly complex technologies (as proxied by either large payments on patents or high capital intensity). A large technology gap *per se* does not appear to hinder technology spillovers on average, although industries with large technology gaps and a high foreign presence experience lower spillovers than other industries.⁴

Kokko et al. (1996) hypothesise that domestic firms can only benefit if the technology gap between the multinational and the domestic firm is not too wide so that domestic firms can absorb the knowledge available from the multinational. Thus domestic firms using very backward production technology and low skilled workers may be unable to learn from multinationals. Using a cross-section of firm-level data for

number of recent studies on the UK (for example, Girma et al., 2001, Girma and Wakelin, 2001, Haskel et al., 2002). None of the studies analyses the role of absorptive capacity in such detail as done in this paper.
4 Kokko (1994) argues that these industries show many of the characteristics of being “enclaves” where multinationals have little interaction with domestic firms and, hence, there is little scope for spillovers.

Uruguay, Kokko et al. find evidence for productivity spillovers to domestic firms with moderate technology gaps, (measured as the difference between the firm's labour productivity and the average labour productivity in foreign firms) but not for firms which use considerably lower levels of technology.⁵

Girma et al. (2001) use firm-level panel data to examine productivity spillovers in UK manufacturing. They find evidence for spillovers to firms with a low difference between the firm's productivity level and the industry frontier productivity level (termed "technology gap"). Firms with a technology gap of 10 per cent or less appear to increase productivity with increasing foreign presence in the industry, while firms with higher gaps seem to suffer reductions in productivity.

These papers define absorptive capacity as a technology gap defined in terms of productivity differentials between foreign and domestic firms. This is motivated by the idea that domestic firms with productivity levels similar to multinationals' may also be more capable of absorbing the transferred technology. Other definitions of absorptive capacity have been put forward, however. For example, Kinoshita (2001) finds evidence for positive spillovers from FDI to local firms that are R&D intensive in her analysis of firm level panel data for the Czech Republic. She interprets firms' R&D intensity as a measure of absorptive capacity. Barrios and Strobl (2002) also take R&D active domestic firms as having absorptive capacity. Furthermore, they argue that exporting firms are more exposed to competition on foreign markets and may, therefore, be likely to have higher levels of technology, and thus absorptive capacity, than non-exporters. In

⁵ By contrast, Sjöholm (1999) finds that, in cross-sectional data for Indonesian manufacturing firms, productivity spillovers from foreign to domestic firms are larger the larger the technology gap (also defined in terms of differences in labour productivity) between those groups of firms and the higher the degree of competition in the industry.

their empirical analysis, using firm level panel data for Spain, they find that, indeed, exporters benefit more from FDI spillovers, but that there is no apparent absorptive capacity effect for R&D active firms relative to those that are not R&D active.

3 Econometric model and estimation technique

3.1 Modelling productivity spillovers from FDI

Empirical studies on productivity spillovers commonly regress firm level productivity on a number of covariates, including foreign presence in the industry. This implies the constraint that all firms benefit equally from spillovers, *ceteris paribus*. In this paper we allow the spillover effect to vary across plants according to their level of absorptive capacity (ABC). Specifically, to investigate the role of absorptive capacity we estimate the impact of FDI spillovers on productivity via the following total factor productivity (TFP) growth equation,

$$\Delta TFP_{it} = \alpha TFP_{it-1} + \beta' X_{it-1} + \gamma(ABC)\Delta FDI_{jrt} + D_{rt} + \varepsilon_{it} \quad (1)$$

which can be rewritten as

$$TFP_{it} = (1 + \alpha)TFP_{it-1} + \beta' X_{it-1} + \gamma(ABC)\Delta FDI_{jrt} + D_{rt} + \varepsilon_{it} \quad (2)$$

which forms the basis for our empirical work. Here i, j, r and t index firms, four-digit industries, regions and time periods respectively; TFP_{it-1} captures initial level of TFP, and X is a vector of variables hypothesised to impact on plant level TFP growth trajectories, namely plant age and a measure of four-digit industry concentration (Herfindhal index).⁶ FDI is a vector that consists of two variables capturing four-digit industry foreign presence in the firm's region and outside the region, D denotes the full

⁶ The Herfindahl index is calculated based on plant's market shares in terms of employment shares.

set of regional and time dummies and ε is a random error term. The use of regional dummies helps mitigate concerns that, within a sector, the regional location of FDI might be correlated with factors that also affect plants' productivity.

If absorptive capacity matters for the pattern of FDI-induced TFP growth, the spillovers regression functions will not be identical across all domestic firms. For this reason the coefficient on the FDI vector in the above equations is explicitly made to depend on absorptive capacity (ABC), which is defined as

$$ABC_{it} = TFP_{it-1} / \max_{industry} (TFP_{jt-1}) \quad (3)$$

that is, establishment i 's TFP relative to the maximum TFP in the four digit sector (the "industry leader").⁷ A high level of absorptive capacity is supposed to indicate technological congruity with industry leaders, which are predominantly foreign plants in the data.

In order to capture possible non-linearities we allow the parameter capturing the degree of spillovers, γ , to be a quadratic function of the firm specific level of absorptive capacity,

$$\gamma = d_0 + d_1 ABC + d_2 ABC^2 \quad (4)$$

where the d 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 the *rate* at which FDI-induced productivity grows to vary with absorptive capacity. For

⁷ As discussed above, other measures of absorptive capacity have been employed in the literature, such as R&D, export activity. Due to data availability we focus on the relative productivity measure. This measure may also be most appropriate as it determines the relative efficiency of the plant. Note also that, since we define absorptive capacity as a relative concept, i.e., each establishment's distance from the industry leader, this should not lead to problems if the industry leader is an extreme outlier or changes over time.

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 (or turning point) $ABC = -(d_1/2d_2)$.

Allowing for this quadratic relationship takes account of the idea that firms with either very low or very high levels of absorptive capacity may be least likely to benefit from spillovers, as they either do not have the technological ability or are too similar in their technology to the MNCs to be able to benefit from spillovers. A similar argument has been put forward by Gomulka (1990) in the context of the technological catch-up of countries.

3.2 Quantile regression

Recent empirical studies of firm-level productivity dynamics have established that there is large and persistent heterogeneity across firms even within narrowly defined industries, and that the amount of change in the productivity distribution is not trivial.⁸ This has an important but previously unrecognised implication for productivity growth empirics: standard OLS or GMM techniques which concentrate on the conditional mean function of the dependent variable are unlikely to be adequate analytical tools. In the presence of heterogeneous productivity processes, it is more appropriate (and arguably more interesting) to examine the dynamics of productivity at different points of the distribution rather than “average” properties (i.e. conditional means).

To do this, we employ the quantile regression technique introduced by Koenker and Bassett (1978). Denoting the vector of regressors in equation (2) by Z , the quantile regression model can be written as

$$TFP_{it} = Z'_{it}\beta_{\theta} + \varepsilon_{\theta it}, \quad Quant_{\theta}(TFP_{it} | Z_{it}) = Z'_{it}\beta_{\theta} \quad (5)$$

where $Quant_{\theta}(TFP_{it} | Z_{it})$ denotes the conditional quantile of TFP. The distribution of the error term ε_{θ} is left unspecified, so the estimation method is essentially semiparametric.⁹ The θ^{th} quantile regression, $0 < \theta < 1$, solves

$$\min_{\beta} \frac{1}{n} \left\{ \sum_{i,t:TFP \geq z'\beta} \theta |TFP_{it} - Z'_{it}\beta| + \sum_{i,t:TFP < z'\beta} (1-\theta) |TFP_{it} - Z'_{it}\beta| \right\} \dots (6)$$

As one keeps increasing θ from 0 to 1, one can trace the entire conditional distribution of plant level productivity, conditional on the set of regressors. Thus quantile regressions allow us to focus attention on specific parts of the productivity distribution, and help us answer questions like ‘what are the FDI-induced externalities to firms below the 10th percentile level of TFP?’ This is a practically important question, since different responses to FDI may be expected from firms at different points of the productivity distribution.

Furthermore, another advantage of quantile methods is that they provide a more robust and efficient alternative to least squares estimators when the error term is non-normal. This may be important here since establishment level TFP does not appear to be (log)normally distributed. Figure 1 shows, for the years 1980 and 1992, Kernel density estimates of log TFP and the corresponding normal density if the data were normally distributed. There are departures from normality apparent, in particular for the electronics sector. Table 1 shows some more detailed summary statistics and the p-values for two tests of normality. In all cases we can reject the null hypothesis that log TFP be normally distributed.

⁸ See Bartelsman and Doms (2000) for a comprehensive review.

[Figure 1 and Table 1 here]

Since the data set contains a finite number of observations, only a finite number of quantiles are distinct. In this study we consider regression estimates at five different quantiles, namely, the 10th, 25th, 50th (median), 75th and 90th percentiles of the TFP distribution. The use of an absorptive capacity proxy in the set of regressors implies that, even within a particular conditional quantile, the response of plant level productivity growth to FDI will vary according to initial level of productivity.

3.3 TFP estimation

For the estimation of equation (2) we need to have reliable estimates of plant level TFP. Whatever the object of the productivity analysis, it is always important to obtain consistent TFP estimates. Using log values, we write the production function as $y_{it} \equiv f(l_{it}^s, l_{it}^u, k_{it}, m_{it}, TFP_{it})$, where y is output and there are four factors of production: skilled labour (l^s), unskilled labour (l^u), materials or cost of goods sold (m) and capital stock (k). For estimation purposes we employ a first-order Taylor approximation and write the production function as:

$$y_{it} = \beta_0 + \beta_s l_{it}^s + \beta_u l_{it}^u + \beta_k k_{it} + \beta_m m_{it} + TFP_{it} \quad (7)$$

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

$$TFP_{it} = \rho TFP_{it-1} + \delta D_t + f_i + v_{it} \quad (8)$$

where D is a common year-specific shock, f is a time-invariant firm specific effect and v a random error term. Note that we do not simply model productivity as a fixed effect, as that would imply that TFP differences are fixed, and there is no role for technology diffusion (convergence).

⁹ See Buchinsky (1998) for an overview of quantile models.

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 percent of them have no more than 6 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 estimator to obtain estimates of the factor elasticities, and derive TFP as a residual term. We estimate equation (8) for each of the 49 the four-digit SIC80 industries available in our sample, including subsidiaries of foreign firms to facilitate the computation of the relative technology gaps described in equation (3).¹⁰

4 Data

We use establishment level panel data for UK manufacturing industries from the Annual Respondents Database (ARD) provided by the Office for National Statistics for the empirical analysis. The database is described in more detail in the data appendix. This paper uses data for two broad industries, electronics and mechanical and instrument engineering, spanning 49 four-digit SIC80 industries.¹¹

Since there is evidence of substantial heterogeneity of productivity even within,

¹⁰ The estimations of equation (8) are not reported here to save space. Note that we have a large number of observations even when estimating the equation for each of the 49 four digit sectors; the minimum number of observations is no less than 170.

let alone across sectors, we decided to estimate the equations for different sectors rather than pooling data for the whole manufacturing sector. Our choice of sectors is motivated by the following considerations. First, FDI is important in both sectors. As Griffith and Simpson (2002, Table 4) show, employment in foreign-owned establishments accounted for almost 19 percent of total employment in the electronics sector, and around 15 percent in the engineering sector in 1996. Second, there appears to be evidence of contrasting motives for inward FDI in the two sectors. According to Driffield and Love (2001), R&D activity in the UK engineering industry is greater than R&D intensity in the corresponding sectors in the FDI source countries. This suggests that FDI into this sector might be largely motivated by technology sourcing considerations (see Fosfuri and Motta, 1999). Hence, at least in theory, the scope for technology spillovers may be limited compared to potential spillovers from FDI in the electronics sector, where multinational firms in the UK are known to undertake a significant proportion of their innovative activity in the host country.^{12,13}

We excluded from our regression analysis domestic establishments with zero output, negative capital stock and with no regional information. Table 2 gives the panel structure of the resulting sample of establishments used in this study. A sizeable proportion are only observed once. Our estimation cannot use these due to the need to use lagged variables to construct TFP growth.

[Table 2 here]

¹¹ These are SIC80 industries 33 and 34 (electronics) and 32 and 37 (mechanical and instrument engineering). We refer to the latter as “engineering” throughout the paper.

¹² For example Cantwell and Iammarino (2000) indicate that in semiconductors the share of foreign-owned firms in total patents was over 60 percent for the UK as a whole, and 75 percent for South East England in particular.

¹³ A further advantage is that focusing explicitly on two narrowly defined sectors should mitigate concerns that the location of FDI in a sector might be correlated with factors affecting plants’ productivity.

Foreign penetration is defined as the proportion of employment in the *four-digit industry* accounted for by foreign multinationals. We have four-digit region-specific FDI variables, and a distance-weighted measure of foreign presence outside the region but within the same sector. Here we follow the literature on neighbourhood agglomeration (Adsera, 2000), and for a firm in region r and industry j this is defined as

$$OUTFDI_{rj} = \sum_{k \neq r} FDI_{kj} / d_{kr}^2, \text{ where } d_{kr} \text{ is the distance (in miles) between the largest cities}$$

in regions k and r . Note that equation (2) includes the *change* in the FDI variables as covariates.

5 Empirical results

Estimates of plant level TFP were calculated as described in equations (7) and (8). These were then used in the productivity spillovers estimations of equation (2), the results of which are presented in Tables 3 and 4 for the electronics and engineering sector respectively. The tables give results for estimations of the conditional mean as well as for the 10th, 25th, 50th (median), 75th and 90th quantile of the TFP distribution.

Overall, while the results in terms of the signs of the coefficients seem to be fairly similar across quantiles and between sectors, there is apparent heterogeneity in the statistical significance and magnitude of the coefficients. For example, the conditional mean regression for the electronics sector shows no statistically significant effect of FDI in the region on TFP growth, while there is evidence for a positive direct effect, as well as a significant effect through the interaction term of regional FDI on TFP for establishments in the engineering sector. Also, for the electronics sector, the effect of regional FDI seems to be larger (in terms of the size of the coefficient) for establishments

in the 90th quantile compared to the median. This effect is mirrored for the engineering sector.

[Tables 3 and 4 here]

It is, of course, difficult to assess the size of the actual effect of FDI on productivity for establishments in the different quantiles of the TFP distribution, not least due to the inclusion of the interaction terms. Establishments that fall within the different quantiles of the TFP distribution may also be expected to have different levels of absorptive capacity. To calculate the effect of FDI at the different quantiles for a given level of absorptive capacity we proceed as follows. First, we calculate the q^{th} quantile ($q = 10, 25, 50, 75, 90$) of the TFP distribution and construct a 90 percent confidence interval around that value. Second, we calculate the median absorptive capacity level for establishments within the 90 percent confidence interval of the q^{th} quantile. The results are shown in Table 5. It is noteworthy that the median absorptive capacity level is higher for the electronics sector for all quantiles, although electronics only has higher TFP in the lower quantiles of the distribution up to the median. This may suggest that, in this sector, there is less of a productivity differential between foreign and domestic establishments.

[Table 5 here]

We use the median values for absorptive capacity shown in Table 5 to calculate the marginal effect of an increase in the growth of FDI in or outside the region. The marginal effects, which are presented in Table 6, are evaluated at the median absorptive capacity level for the various quantiles. For example, the figures in the table show that, for an establishment in the electronics sector with median level of absorptive capacity, a 1

percentage point increase in the growth of FDI in the region will lead to a 0.9 percent increase in the growth of TFP.¹⁴

[Table 6 here]

The table shows significant differences in the size of the marginal effects across quantiles and sectors.¹⁵ For FDI in the region, the largest effects are apparent for the 90th quantile both for the electronics and engineering sector. Interestingly, establishments in the 10th quantile in the electronics sector benefit more (in terms of the absolute size of the marginal effect) than those in the 25th or median quantile. This suggests that domestic establishments in either the higher or lower end of the TFP distribution are set to benefit more from FDI spillovers than firms in the middle range of the distribution.

While we find that the effect of an increase in the growth of FDI in the region has a consistently positive effect on TFP growth in all quantiles, the marginal effects of FDI outside the region is largely negative. These results mirror those of Driffield (2001) who, using industry level data for UK manufacturing, also found a positive effect of FDI in the same region and industry, but a negative effect of FDI in the same sector but outside the region. He argued that this is consistent with a negative competition effect from multinationals outside the region, which is not offset by positive spillovers which appear to be more prevalent at the local level. While this explanation seems appealing it is, however, not possible to determine with any certainty the reasons for such negative spillover effects from FDI outside the region with our data.

While the effect of changes in FDI for a *given level* of absorptive capacity is informative in its own right we are more interested in the impact of changes of absorptive

¹⁴ That is, from 0.791 (= $\exp(-0.235)$) to 0.800.

¹⁵ The marginal effect equals 0 if the regression coefficients are not statistically significant.

capacity on establishments' ability to benefit from spillovers. In order to tackle this issue we, firstly, turn back to the regression results in Tables 3 and 4 to determine the shape of the relationship between absorptive capacity and TFP growth. From the coefficients on the interaction terms we see that, for both sectors and most quantiles, there is a convex (u-shape) relationship for the interaction of absorptive capacity with FDI in the region. Hence, for a given level of FDI growth, increases in absorptive capacity will first reduce but eventually increase productivity growth. This pattern is not as consistent across quantiles for FDI outside the region although, for those cases for which both interaction terms are statistically significant, they indicate a concave (inverted u-shape) relationship.

The former result is at first sight not in line with our expectation, as pointed out above, that firms with high and low levels of absorptive capacity are least likely to benefit from FDI. The latter result, however, appears to be as expected. In order to rationalise the results, we should, however, take into account that the two relationships may reflect the counteracting effects of positive spillovers and negative competition effects, as discussed by Aitken and Harrison (1999). While we would expect positive spillover effects mainly from FDI within the region, due to the geographical dimension to knowledge flows, competition between multinationals and domestic firms may be strong even if the two establishments are located far away from each other. If we accept this, we can interpret the two relationships as follows.

For FDI within the region, domestic firms with low absorptive capacity levels are not able to benefit from positive spillovers (as expected) but are also unlikely to be in direct competition with multinationals due to their relative backwardness. As firms

improve their absorptive capacity by becoming more productive they start competing with multinationals (thus beginning to be exposed to the negative competition effect) but are not yet able to benefit from spillovers. Only as they improve their absorptive capacity beyond the critical value are they able to benefit from positive spillovers, which then outweigh the negative competition effect as they become more able to compete with the multinationals.

As regards FDI outside the region domestic firms with low levels of absorptive capacity are not able to benefit from spillovers but may also not be in competition with multinationals. Only as they become more efficient and close the technology gap do they start benefiting from weak positive spillovers. The competition effect will then outweigh any weak positive spillover effects as establishments increase their levels of absorptive capacity and are less likely to learn more from multinationals.

To be more precise about the shapes of the functions we can calculate the critical values (turning points) at which the effect of *ABC* on productivity spillovers switches from negative to positive (for regional FDI) or vice versa (for FDI outside the region). These calculations for the two sectors and various quantiles are given in Table 7. The first result to note is that the critical values are all around 0.5 for all quantiles in both sectors. For example, we find for the electronics sector that establishments having productivity levels around the 25th quantile start to benefit from increasing growth of FDI in the region once they achieve an absorptive capacity level of over 0.49. Below this threshold they will experience a negative productivity growth effect. From Table 5 we know that the median absorptive capacity level of establishments in the 25th quantile is 0.40, which is well below the critical value. This implies that those 50 percent of

establishments with absorptive capacity levels below this value will experience negative growth effects if the growth of FDI in the region increases. As a matter of fact, our summary statistics (which are not reported in this paper) show that over 70 percent of establishments in the 25th quantile of the TFP distribution have absorptive capacity levels below the critical value.

[Table 7 here]

Comparisons of Table 7 and Table 5 show that, indeed, for all cases for which we can calculate turning points, the median value of the productivity gap is below the critical value. This implies that more than 50 percent of establishments with productivity levels in these quantiles are negatively affected by a growth in the change of FDI in the region.

For the two cases for which we can calculate turning points for the effect of absorptive capacity and FDI outside the region we also find that the critical value is at a higher value than the median absorptive capacity. Now, however, this indicates that more than 50 percent of firms benefit from increases in the change of FDI outside the region by increasing productivity growth. Only establishments with levels of absorptive capacity of more than the critical value would experience negative changes in productivity growth following increases in the growth of FDI outside the region.

Using the regression results in Tables 3 and 4 we can calculate the marginal effects of changes in absorptive capacity for a given level of growth of FDI. Such a calculation enables us to say something about the effect on productivity growth of improving absorptive capacity levels in the host country. The results of these calculations are charted in Figures 2a to 2d. Figure 2a shows the marginal effect of changes in absorptive capacity on productivity growth for a given level of FDI growth for

the electronics sector.¹⁶ These marginal effects are equal to zero at the critical values shown in Table 7. For the quantiles for which we find a quadratic relationship between absorptive capacity and productivity we find that establishments in the 90th quantile appear to benefit most from increasing absorptive capacity beyond the turning point. However, they also show the largest negative effects on productivity growth for absorptive capacity levels below the critical value. These results are broadly similar for the engineering sector (Figure 2.b).

Figures 2.c and 2.d chart the corresponding results for changes in absorptive capacity for a given increase in FDI outside the region for the various quantiles for which we determined a statistically significant relationship. In the case of FDI outside the region we find that establishments in the higher quantiles (in both electronics and engineering) show the highest positive marginal effects for levels of absorptive capacity lower than the turning point. Having reached the critical value these establishments are, however, those which show the largest negative effects on productivity growth of increases in absorptive capacity.

[Figures 2.a – 2.d here]

6 Conclusions

This paper focuses on the role of absorptive capacity in determining whether or not domestic establishments benefit from productivity spillovers from FDI. We analyse this issue using establishment level data for the electronics and engineering sectors in the UK. Absorptive capacity is measured as the difference in TFP between an establishment and the maximum TFP in the industry. We distinguish the effect of FDI in the same

¹⁶ In all graphs we assume this FDI growth to be 0.1, a figure that is well within the range of actual values

sector and region as the establishment, from FDI in the same sector but outside the region. We also allow for different effects of FDI on establishments located at different quantiles of the productivity distribution by using conditional quantile regression.

Overall, while there is substantial heterogeneity in results across sectors and quantiles, our findings clearly suggest that both absorptive capacity and distance matter for productivity spillover benefits. We find that there is a u-shaped relationship between absorptive capacity and productivity spillovers from FDI in the region in many cases, while there is an inverted u-shape relationship for spillovers from FDI outside the region. The former result indicates that improvements in absorptive capacity at the level of the establishment may enhance its ability to benefit from spillovers from FDI located within the same region. However, the latter results show that an opposite effect is at work for FDI located outside the region, where establishments with high levels of absorptive capacity may lose most (in terms of reductions of productivity growth) due to spillovers. This pattern seems consistent with the idea that positive productivity spillovers from FDI are localised and only establishments located within the same region are set to benefit. If FDI is located far away from the establishment the negative competition effect of FDI appears to dominate, however. While our data and estimation strategy do not allow us to determine in any detail such a possible competition effect, the investigation of this issue appears to be a fruitful topic for future research.

The importance of absorptive capacity for determining the potential benefits for domestic firms from FDI suggests a role for policy makers. Host country policies may be targeted at enabling domestic firms to build up their absorptive capacity through providing incentives for training and R&D in domestic firms. Also, at a more general

for FDI growth in the data

level, policies may be aimed at providing the necessary stock of human capital in the economy through appropriate education and training policies in order to upgrade general skills.

References

- Adsera, A. (2000), "Sectoral spillovers and the price of land: a cost analysis", *Regional Studies and Urban Economics*, Vol. 30, pp. 565-585.
- Aitken, B.J. and A.E. Harrison (1999), "Do Domestic Firms Benefit from Direct Foreign Investment? Evidence from Venezuela", *American Economic Review*, Vol. 89, pp. 605-618.
- Audretsch, D.B. (1998), "Agglomeration and the location of innovative activity", *Oxford Review of Economic Policy*, Vol. 14, pp. 18-29.
- Baltagi, B.H. and J.M. Griffin (1997), "Pooled estimators versus their heterogeneous counterparts in the context of the dynamic demand for gasoline", *Journal of Econometrics*, Vol. 77, pp. 303-327.
- Barnes, M. and R. Martin (2002), "Business Data Linking: An Introduction", *Economic Trends*, No. 581, pp. 34-41.
- Barrios, S. and E. Strobl (2002), "Foreign direct investment and productivity spillovers: evidence from the Spanish experience", *Weltwirtschaftliches Archiv*, Vol. 138, pp. 459-481.
- Bartelsman, E.J. and M. Doms (2000), "Understanding productivity: lessons from longitudinal microdata", *Journal of Economic Literature*, Vol. 38, pp. 569-595.
- Blomström, M. and A. Kokko (1998), "Multinational corporations and spillovers", *Journal of Economic Surveys*, Vol. 12, pp. 247-277.
- Buchinski, M.(1998), "Recent advances in quantile regression models", *Journal of Human Resources*, Vol. 33, pp. 88-126.
- Cantwell, J and S. Iammarino (2000), "Multinational corporations and the location of technological innovation in the UK regions", *Regional Studies*, Vol. 34, pp. 317-332.
- D'Agostino, R.B., A. Balanger and R.B. D'Agostino Jr. (1990), "A suggestion for using powerful and informative tests of normality", *American Statistician*, Vol. 44, pp. 316-321.
- Driffield, N. (2001), "Regional policy and the impact of FDI in the UK", in Pain, N. (ed.), *Inward investment, technological change and growth*, Basingstoke: Palgrave.
- Driffield, N, and J. Love (2001), "Does the motivation for foreign direct investment affect productivity spillovers to the domestic sector?", mimeo, University of Birmingham.
- Dimelis, S. and H. Louri (2002), "Foreign direct investment and efficiency benefits: a conditional quantile analysis", *Oxford Economic Papers*, Vol. 54, pp. 449-469.
- Findlay, R. (1978), "Relative backwardness, direct foreign investment, and the transfer of technology: a simple dynamic model", *Quarterly Journal of Economics*, Vol. 92, pp. 1-16.
- Fosfuri, A. and M. Motta (1999), "Multinationals without advantages", *Scandinavian Journal of Economics*, Vol. 101, pp. 617-630.

- Girma, S., D. Greenaway and K. Wakelin (2001), "Who benefits from foreign direct investment in the UK?", *Scottish Journal of Political Economy*, Vol. 48, pp. 119-133.
- Girma, S. and K. Wakelin (2001), "Regional underdevelopment: is FDI the solution? A semiparametric analysis", CEPR Discussion Paper 2994.
- Glass, A. and K. Saggi (1998), "International technology transfer and the technology gap", *Journal of Development Economics*, Vol. 55, pp. 369-398.
- Gomulka, S. (1990), *The theory of technological change and economic growth*, London: Routledge.
- Görg, H. and D. Greenaway (2002), "Much ado about nothing? Do domestic firms really benefit from foreign direct investment?", CEPR Discussion Paper 3485.
- Görg, H. and E. Strobl (2001), "Multinational companies and productivity spillovers: a meta-analysis", *Economic Journal*, Vol. 111, pp. F723-F739.
- Griffith, R. and H. Simpson (2002), "Characteristics of foreign-owned firms in British manufacturing", in Blundell, R., D. Card and R. Freeman (eds.), *Creating a Premier League Economy*, Chicago: Chicago University Press.
- Haskel, J.E., S.C. Pereira and M.J. Slaughter (2002), "Does inward foreign direct investment boost the productivity of domestic firms?", CEPR Discussion Paper 3384.
- Head, K. (1998), "Comment on 'Comparing Wages, Skills, and Productivity between Domestically and Foreign-Owned Manufacturing Establishments in the United States'", in Baldwin, R., R. Lipsey and J.D. Richardson (eds.), *Geography and Ownership as Bases for Economic Accounting*, Chicago: Chicago University Press, pp. 255-258.
- Keller, W. (2001), "International technology diffusion", CEPR Discussion Paper 3133.
- Kinoshita, Y. (2001), "R&D and technology spillovers through FDI: innovation and absorptive capacity", CEPR Discussion Paper 2775.
- Koenker, R. and G. Bassett (1978), "Regression quantiles", *Econometrica*, Vol. 50, pp. 43-61.
- Kokko, A. (1994), "Technology, market characteristics, and spillovers", *Journal of Development Economics*, Vol. 43, p. 279-293.
- Kokko, A., R. Tansini and M.C. Zejan (1996), "Local technological capability and productivity spillovers from FDI in the Uruguayan manufacturing sector", *Journal of Development Studies*, Vol. 32, pp. 602-611.
- Pesaran, M.H. and R. Smith (1995), "Estimating long-run relationship from dynamic heterogeneous panels", *Journal of Econometrics*, Vol. 68, pp. 79-112.
- Shapiro, S.S. and R.S. Francia (1972), "An approximate analysis of variance test for normality", *Journal of the American Statistical Association*, Vol. 67, pp. 215-216.
- Sjöholm, F. (1999), "Technology gap, competition and spillovers from direct foreign investment: evidence from establishment data", *Journal of Development Studies*, Vol. 36, pp. 53-73.

Data Appendix

The ARD consists of individual establishments' records that underlies the Annual Census of Production. As Barnes and Martin (2002) provide a very useful introduction to the data set, we only include a brief discussion of some of the features of the data that are relevant to the present work. For each year the ARD consists of two files. What is known as the 'selected file', contains detailed information on a sample of establishments that are sent inquiry forms. The second file comprises the 'non-selected' (non-sampled) establishments and only basic information such as employment, location, industry grouping and foreign ownership status is recorded. Some 14,000-19,000 establishments are selected each year, based on a stratified sampling scheme. The scheme tends to vary from year to year, but for the period under consideration establishments with more than 100 employees were always sampled.

In the ARD, an establishment is defined as the smallest unit that is deemed capable of providing information on the Census questionnaire. Thus a 'parent' establishment reports for more than one plant (or 'local unit' in the parlance of ARD). For selected multi-plant establishments, we only have aggregate values for the constituent plants. Indicative information on the 'children' is available in the 'non-selected' file.

Like the majority of researchers using the ARD (e.g., Haskel et al., 2002) we use data on multi-plant establishments as they are. In our sample period (1980-92), about 95 percent of the establishments in these industries are single-plant firms. In the actual sample we used for the econometric estimation this figure is around 80 percent. Hence, most of the data used is actually plant level data and we, therefore tend to use the terms plant and establishment interchangeably.

There are, however, two important ways in which we have made use of the local unit information in the non-selected file. The first is in the construction of measures of regional FDI. Foreign presence in a region and sector is defined as the proportion of employment accounted for by foreign multinationals. Simply relying on establishment data could be misleading, as they could report for plants across different regions or sectors. However, by extracting the employment, ownership and industrial affiliation data of the ‘children’ in the ‘non-selected’ file, it was possible to calculate correctly the regional FDI variables. The second way information in the non-selected file was used is in the identification of single location (region) and multiple location establishments.

Table 1: Summary statistics for log TFP

	all observations	Engineering 1980	Engineering 1992	Electronics 1980	Electronics 1992
mean	0.004	-0.005	0.011	0.005	0.016
std.dev.	0.379	0.525	0.472	0.221	0.280
skewness	-19.163	-20.056	0.222	0.372	-0.358
kurtosis	753.977	560.842	-16.350	4.966	16.236
10 th quantile	-0.257	-0.265	-0.248	-0.240	-0.236
25 th quantile	-0.136	-0.145	-0.120	-0.125	-0.125
median	-0.010	-0.013	0.006	-0.013	0.001
75 th quantile	0.133	0.134	0.159	0.124	0.130
90 th quantile	0.303	0.304	0.324	0.271	0.296
Observations	40432	2112	1821	857	1022
test1 (p-value)	--	0.000	0.000	0.000	0.000
test2 (p-value)	0.000	0.000	0.000	0.000	0.000

Notes: test1: test for normality (Shapiro and Francia, 1972)
test2: skewness and kurtosis test for normality (D'Agostino et al, 1990)

Table 2: Number of domestic plants by number of years observed

Years	Electronics		Engineering	
	# plants	%	# plants	%
1	807	27.19	2078	30.32
2	514	17.32	1203	17.55
3	316	10.65	776	11.32
4	245	8.25	572	8.35
5	197	6.64	468	6.83
6	150	5.05	378	5.52
7	134	4.51	269	3.93
8	98	3.3	221	3.22
9	97	3.27	181	2.64
10	72	2.43	155	2.26
11	72	2.43	127	1.85
12	94	3.17	147	2.15
13	172	5.8	278	4.06
Total	2968	100	6853	100

Table 3: Regression results for electronics sector.
Dependent variable: log TFP

	mean	10 th quantile	25 th quantile	median	75 th quantile	90 th quantile
Lagged TFP	0.391** (0.010)	0.590** (0.012)	0.663** (0.006)	0.730** (0.006)	0.746** (0.010)	0.714** (0.027)
Age	-0.001 (0.001)	0.003** (0.001)	0.001 (0.001)	-0.001 (0.001)	-0.002** (0.001)	-0.005** (0.001)
Herfindahl index	-0.065 (0.065)	-0.231** (0.074)	-0.150** (0.045)	-0.034 (0.038)	0.031 (0.049)	0.161* (0.080)
FDI in region	0.165 (0.166)	0.227 (0.196)	0.201+ (0.109)	0.317** (0.093)	0.163 (0.137)	0.552+ (0.313)
FDI in region * ABC	-0.612 (0.615)	-1.091 (0.744)	-0.845* (0.402)	-1.243** (0.342)	-0.512 (0.486)	-2.103** (1.077)
FDI in region * ABC squared	0.575 (0.531)	1.173+ (0.647)	0.855** (0.340)	1.147** (0.291)	0.451 (0.400)	1.848** (0.852)
FDI outside region	0.244 (0.166)	-0.104 (0.181)	-0.136 (0.119)	-0.093 (0.093)	-0.035 (0.142)	-0.126 (0.292)
FDI outside region * ABC	-1.062+ (0.621)	0.494 (0.692)	0.649 (0.457)	0.503 (0.351)	0.254 (0.533)	0.324 (1.065)
FDI outside region * ABC squared	1.003+ (0.542)	-0.546 (0.633)	-0.730+ (0.417)	-0.573+ (0.307)	-0.267 (0.463)	-0.117 (0.897)
observations	8650	8650	8650	8650	8650	8650

Notes: standard error in parentheses
significant at ** 1 percent, * 5 percent, + 10 percent level
regressions include time trend and regional dummies

Table 4: Regression results for engineering sector.
Dependent variable: log TFP

	mean	10 th quantile	25 th quantile	median	75 th quantile	90 th quantile
Lagged TFP	0.314** (0.008)	0.591** (0.007)	0.674** (0.003)	0.846** (0.003)	0.729** (0.006)	0.684** (0.018)
Age	-0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	0.005** (0.001)	-0.002** (0.001)	-0.004** (0.001)
Herfindahl index	0.016 (0.070)	-0.114* (0.059)	-0.067* (0.030)	-0.194** (0.025)	0.019 (0.032)	0.038 (0.059)
FDI in region	0.763+ (0.416)	0.385 (0.751)	0.286 (0.254)	-0.751** (0.146)	0.931** (0.163)	1.208** (0.276)
FDI in region * ABC	-3.133+ (1.655)	-1.290 (2.852)	-0.892 (0.982)	-0.055 (0.553)	-4.444** (0.610)	-6.500** (1.075)
FDI in region * ABC squared	2.873+ (1.489)	1.034 (2.469)	0.633 (0.852)	1.456** (0.468)	4.367** (0.539)	6.323** (1.044)
FDI outside region	-1.028* (0.425)	-0.326 (0.793)	-0.310 (0.263)	0.349* (0.149)	-0.992** (0.163)	-1.543** (0.273)
FDI outside region * ABC	4.169** (1.672)	1.094 (2.958)	1.083 (0.997)	-0.160 (0.056)	4.683** (0.599)	7.025** (1.003)
FDI outside region * ABC squared	-3.776** (1.488)	-0.990 (2.484)	-0.864 (0.839)	-0.227 (0.458)	-4.591** (0.515)	-6.510** (0.922)
observations	16114	16114	16114	16114	16114	16114

Notes: standard error in parentheses
significant at ** 1 percent, * 5 percent, + 10 percent level
regressions include time trend and regional dummies

Table 5: Mean ABC for firms within the 90 percent confidence interval of q^{th} quantile of log TFP

	TFP	90% confidence interval for TFP		median ABC
<i>Electronics</i>				
Mean	0.009	0.005	0.013	0.441
10 th quantile	-0.235	-0.240	-0.230	0.391
25 th quantile	-0.127	-0.131	-0.123	0.404
median	-0.007	-0.010	-0.004	0.442
75 th quantile	0.128	0.124	0.132	0.485
90 th quantile	0.290	0.285	0.298	0.515
<i>Engineering</i>				
Mean	0.001	-0.003	0.005	0.399
10 th quantile	-0.267	-0.271	-0.263	0.307
25 th quantile	-0.142	-0.144	-0.139	0.335
median	-0.011	-0.014	-0.009	0.433
75 th quantile	0.135	0.132	0.139	0.481
90 th quantile	0.308	0.303	0.314	0.464

Table 6: Marginal effect of increase in FDI, evaluated at median ABC

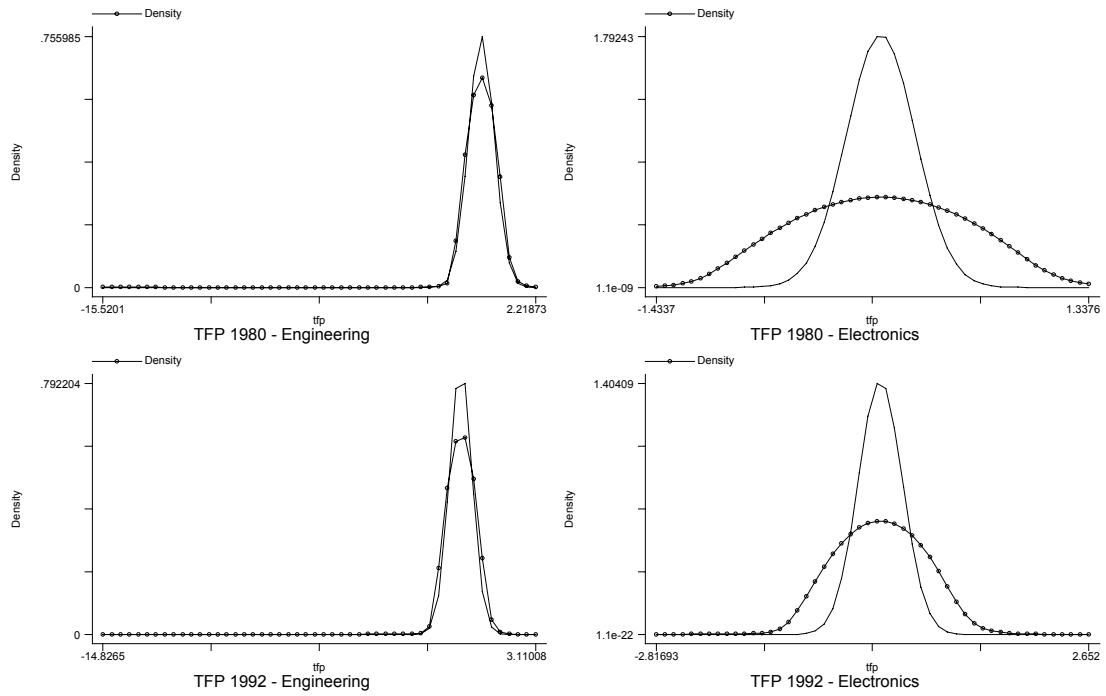
	Electronics		Engineering	
	FDI in region	FDI outside region	FDI in region	FDI outside region
mean	--	0.416	1.806	-1.350
10 th quantile	0.918	--	--	--
25 th quantile	0.551	-0.590	--	--
median	0.782	-0.506	0.510	--
75 th quantile	--	--	2.995	-2.164
90 th quantile	1.373	--	4.060	-2.782

Note: table gives the effect of a one unit increase in FDI on TFP growth, evaluated for the median level of absorptive capacity

Table 7: Calculation of critical values for ABC

	Electronics		Engineering	
	FDI in region	FDI outside region	FDI in region	FDI outside region
mean	--	0.529	0.545	0.552
10 th quantile	--	--	--	--
25 th quantile	0.494	--	--	--
median	0.542	--	--	--
75 th quantile	--	--	0.509	0.510
90 th quantile	0.569	--	0.514	0.540

Figure 1: Kernel density estimates of log TFP

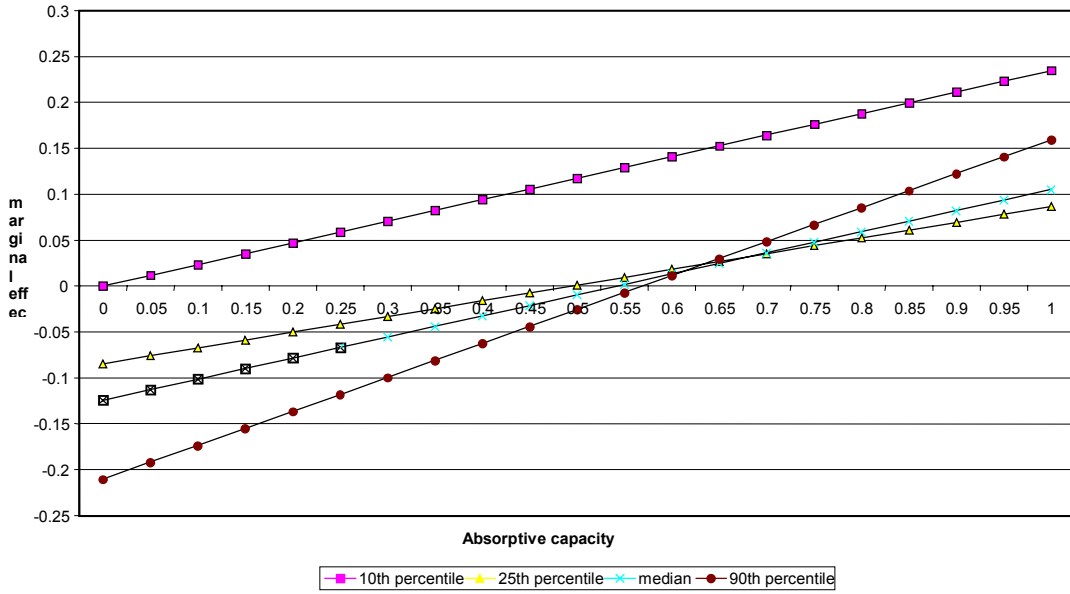


Note: dotted line is density, solid line is normal distribution

Figure 2: Calculation of marginal effects of change in absorptive capacity, evaluated at FDI = 0.1

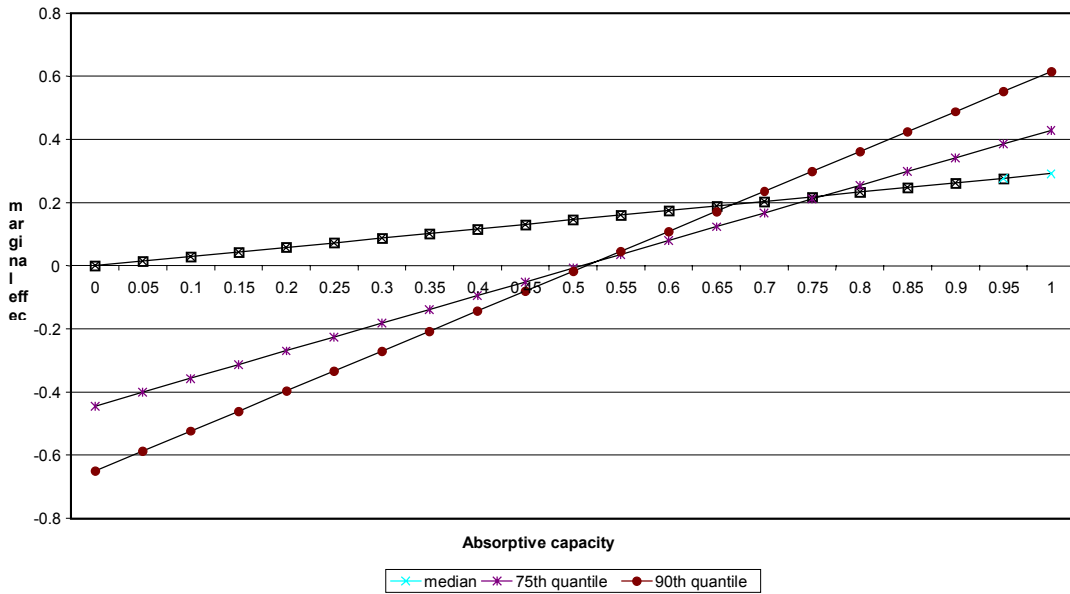
2.a

Electronics - FDI in region



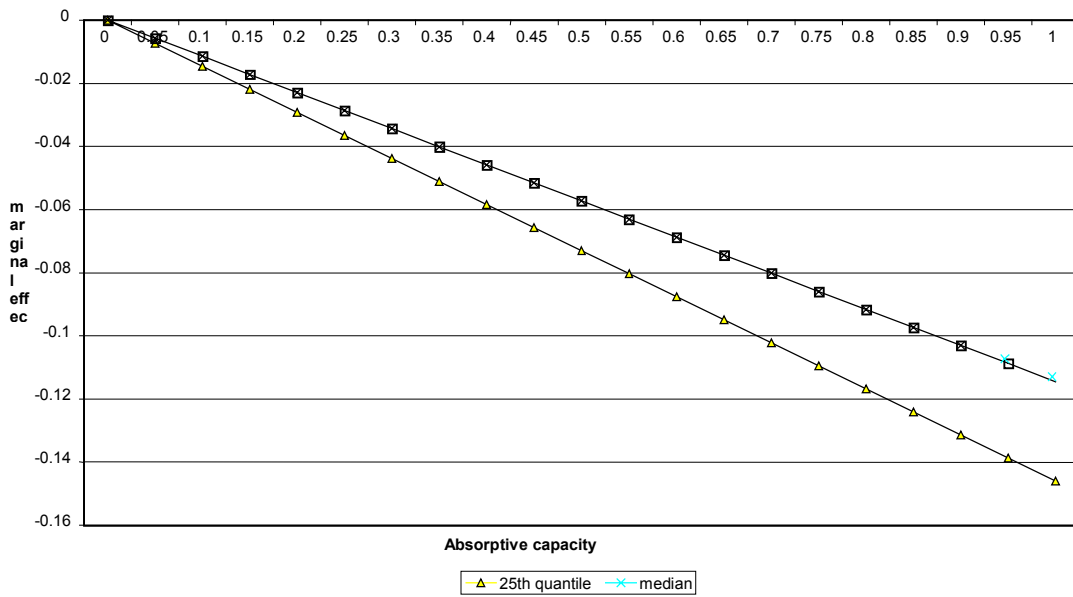
2.b

Engineering - FDI in region



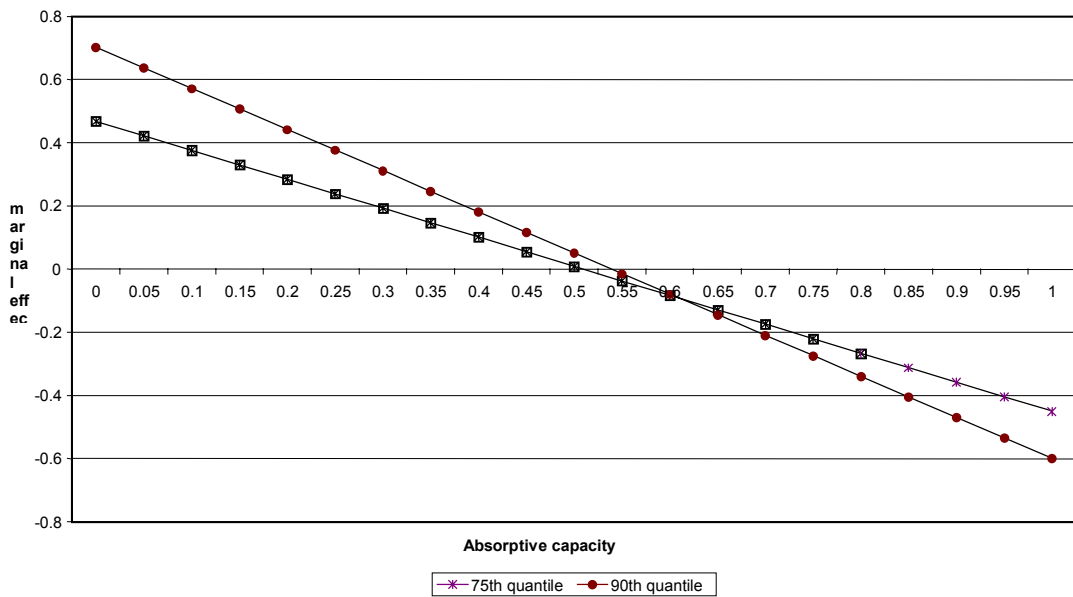
2.c

Electronics - FDI outside region



2.d

Engineering - FDI outside region





Institute for International Integration Studies

The Sutherland Centre, Trinity College Dublin, Dublin 2, Ireland

