

The Impact of Multinational and Domestic Enterprises on Regional Productivity: Evidence from the UK

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26 November 2015

Online at https://mpra.ub.uni-muenchen.de/84926/ MPRA Paper No. 84926, posted 4 March 2018 07:49 UTC The Impact of Multinational and Domestic Enterprises on

Regional Productivity: Evidence from the UK

Abstract

The paper explores the effects of Multinational Enterprises (MNEs) and Domestic

Enterprises (DOMEs), respectively, on regional productivity in the case of UK regions. Our

empirical evidence shows that the more intensive in terms of R&D and intangibles MNEs,

have a stronger effect on regional productivity than DOMEs. However, when we control for

the origin of the MNEs, we find that DOMEs can outperform MNEs from certain countries.

We submit that regions that lag behind can absorb the intangible assets of DOMEs more

readily; and that MNE strategies may not be always aligned to the needs of host regions.

Keywords: Total Factor Productivity (TFP), Regions, Subsidiaries, Domestic Firms, R&D,

Intangibles

JEL Classification: O47, R3, F23

1

Introduction

The relative impact of foreign and domestic firms and investment on regional productivity remains hotly debated. Scholars such as Cantwell and Iammarino (2000), Altomonte and Pennings (2009) and Ke and Lai (2011) have questioned the idea that investments by the subsidiaries of Multinational Enterprises (MNEs thereafter) are more beneficial to regional economic activity, than that of domestic enterprises (DOMEs thereafter). Görg and Greenaway (2004) have surveyed the literature on the impact of MNE activities on domestic firms' productivity highlighting the existence of mixed results that also tend to overestimate the role of MNEs particularly in the context of a developed host economy. For Bode, Nunnenkamp & Waldkirch (2012) the role of MNEs and DOMEs on regional growth could be of comparable importance.

Among developed economies, the UK has been one of the leading recipient countries of Foreign Direct Investment (FDI) (Driffield, Love, Lancheros & Temouri, 2013; Dunning, 1958; United Nations Conference on Trade and Development [*UNCTAD*], 2012). However, inward FDI in the UK has been unequally distributed across regions, potentially contributing to regional disparities which have been substantial and persistent (Rice & Venables, 2003; Dimitratos, Liouka & Young, 2009). This renders the question of the role of DOMEs in laggard regions pertinent.

This paper aims to examine the impact of MNE subsidiaries and DOMEs in the UK within a regional productivity framework over the period 2004-2012. The paper's central contribution to the existing literature is twofold: first, is our analytical framework which models regional Total Factor Productivity (TFP) as a function of regional human capital, and firm specific characteristics from both groups of firms, namely MNE subsidiaries and DOMEs. In this context, we investigate whether TFP gains are subject to a region's ability to absorb knowledge, or its absorptive capacity. In order to test for this idea, we combine

regional and firm level data. This is a novel approach as it allows us to identify the direct impact of MNEs on local economies, based upon structural firm-level information of R&D and intangible assets (IAs). Second, the paper identifies effects associated with the country of origin of the MNEs. To do so, we split the sample of MNEs into four major investor groups namely, US, EU, Japan and the Rest of World (ROW). We hypothesize that this classification can unearth differences in the home-country characteristics of FDI, which may have a differentiated impact on a host- economy's productivity and growth (Görg & Greenaway, 2004; Castellani & Zanfei, 2006). If so, that could allow for a more fine-tuned approach to regional policy making (Buckley, Clegg & Wang, 2007). Finally, our analytical approach cross-fertilizes strands of the productivity and international business (IB) literature to enrich the very limited evidence on the underlying forces of the substantial regional disparities in the context of a developed country (Driffield et al., 2013).

The rest of the paper is organized as follows: section two provides the literature review and hypotheses formulation, section three presents an analytical framework on productivity measurement, the data and empirical modelling, section four presents and discusses our econometric results and section five concludes and discusses policy implications and opportunities for further research.

Literature Review and Hypotheses Development

There is extensive literature on the economic impact of FDI on host countries at a national or regional level, which focuses on productivity gains induced from the technological and managerial superiority of MNEs. These gains can be grouped under four possible channels (Blomström & Kokko, 1998; Liu, Siler, Wang & Wei, 2000; Liu, Ye, Yang, Li & Leipnik, 2014): imitation gains, that are related to technologically mature products and processes, which are superior to those of local firms; skills acquisition gains, where MNEs invest in

specialised human capital in order to implement their business projects and competition and export spillovers, which promote performance and international expansion of local firms.

Dunning's (1993) Ownership, Location, Internalization (OLI) framework, identifies two main types of ownership advantages that help foreign subsidiaries compete successfully in host countries and generate productivity spillovers: (a) possession of intangible assets and (b) the ability of the firm to coordinate its assets and activities. The first set of advantages are known as asset ownership advantages (Oas) and include knowledge expertise and innovation superiority of MNEs, while the second set of advantages is governance-related and refers mainly to "transaction cost minimizing advantages" (Ots) (Dunning, 1993, p. 80). Both types of advantages are strongly associated with multinationality i.e. overseas expansion through FDI, allowing firms to overcome the so-called liability of foreignness (Zaheer, 2015). Accordingly, MNEs are often assumed to outperform DOMEs on the basis of Oas and Ots (Johanson & Vahlne, 2009). New trade theory (Markusen & Venables, 1998) and endogenous growth models (Aghion, Howitt, Brant-Collett, & García-Peñalosa, 1998) show how MNEs improve growth performance of the host economies through transfer of intangible assets such as technological know-how (Barrell & Pain, 1999). Badinger and Tondl (2005) and Dettori, Marrocu, & Paci (2012) - among many others - provide empirical evidence for the positive effect of intangible assets (either in the form of human or social and technological capital) and innovation on regional growth in Europe.

R&D is a key Oa (Dunning & Lundan, 2008). R&D is traditionally perceived as a centralized strategic activity of MNEs performed at the home country of the MNE. Nonetheless, recent MNE strategies involve a more distributed geographically shift of global innovation activities. In this way, MNEs increasingly become major players in generating intangible assets and new knowledge world-wide, hence also in regional economies

(Castellani & Pieri, 2013). This would suggest that MNEs are more important contributors to regional productivity that DOMEs.

On the above basis, our first Hypothesis (H) is formulated as follows

H1: R&D by MNEs has a stronger impact on regional productivity than R&D by DOMEs.

We test the validity of the above hypothesis in two ways. First, we use descriptive evidence to compare R&D intensity between MNEs and DOMEs across 36 UK regions. Second, econometric analysis is employed to test for the hypothesis that R&D activity of MNEs is more important than the R&D of DOMEs for regional productivity.

Apart from R&D, Dunning (1993) identified other forms of Oas, including knowledge capital, product differentiation and marketing capabilities. Denekamp (1995) showed that the possession of IAs provides firms with a major advantage for outward FDI engagement, which helps to overcome the *liability of foreignness* (Zaheer, 2015; Anand & Delios, 1997). Hennart (2009) distinguished between MNEs and DOMEs arguing that the former possess intangible assets while the latter mostly possess locality-based advantages and competences. The impact of IAs on regional growth is well analysed within the literature of regional systems of innovation (Iammarino, 2005; Surinach & Moreno, 2012). More recently, Kramer, Marinelli, Iammarino & Diez (2011) investigated the impact of IAs, namely organization and network capital, on the embeddedness of MNEs in UK regions highlighting conditions under which regions could benefit from MNEs' IAs.

The above motivate our second Hypothesis.

H2: The IAs of MNEs have a stronger impact on regional productivity than the IAs of DOMEs.

Cohen and Levinthal (1990) emphasized the interactive and dynamic interdependence between firms and locations in the context of 'absorptive capacity' (Griffith, Redding & Van Reenen, 2004; López-Bazo, Requena & Serrano, 2006). Absorptive capacity essentially captures that the potential as well as the size of FDI-related gains across regions is analogous to regions' level of absorptive capacity. Importantly, the tacit knowledge embodied in physical and/or IAs of MNEs is transferred to local economies if regions have already possessed an appropriate amount of knowledge. For example, technology diffusion from MNEs take places if local workers, technicians and managers possess appropriate training (Hobday, 2003). The degree of absorptive capacity of regional economies can also determine the degree of "embeddedness" or "stickiness" between subsidiaries and local economies. Markusen (1996) defined "stickiness" as the ability to both attract and retain firm activity at the regional level and argued that the need to make firms commit to a particular region is rather challenging as MNEs always maintain a high degree of mobility in switching production locations. Haskel, Pereira & Slaughter (2007) found that the sustainability of FDIrelated gains is subject to the degree of embeddedness of the MNEs into the local economy. More recently, Murray, Jalette, Bélanger, & Lévesque (2014) addressed the importance of the subsidiary "discretion" in order to alleviate potential relocation whilst Benito, Grogaard & Narula, (2003) argued that FDI-induced effects in high value added activities are maximized for the host economy when MNEs tend to be "sticky".

Regional economies can foster the embeddedness of foreign subsidiaries by developing their own absorptive capacity, which in turn can strengthen the ties of MNEs with local economies either through extensive use of local suppliers or through partnerships such as joint ventures (Birkinshaw & Hood, 2000). The key factor for improving absorptive capacity is via a higher level of human capital. Human capital plays a dual role. First, a higher share of

labour with advanced level of educational attainment improves the production capabilities of the region as skilled workers tend to be more productive and better at creating new technologies (Castellani & Pieri, 2013). This has now been regarded as a stylized fact in empirical growth models (de La Fuente, 2011). Second, human capital leads to better implementation and adoption of existing technologies.

Within the present context, we seek to capture whether regions which are better endowed with human capital benefit from: (i) an autonomous effect and (ii) an absorptive capacity effect. The latter essentially means the higher the level of human capital the higher the gains from R&D activity and intangible capital of MNEs and DOMEs.

Summarizing the above considerations, we put forward the following hypothesis:

H3: The higher is human capital, the higher will be regional TFP.

Buckley et al. (2002) argued that the nationality of MNE is a major determinant of the potential FDI effect on regional performance. Criscuolo and Martin (2009) revealed the superiority of R&D activity undertaken from USA subsidiaries. Gelübcke (2013) investigated the impact of parent country heterogeneity of various foreign subsidiaries operating in Germany. The above studies showed that subsidiaries from different countries of origin can have different business strategies, which in turn can make the contribution of foreign firms to the local economy to vary. The impact of home country can impact upon the strategic behaviour of MNE in a variety of ways, including decisions about innovation and market expansion. Murray et al., (2014) argued that foreign subsidiaries transfer the DNA of their 'home' business systems while Castellani and Zanfei, (2006) identify the impact of "systems of origin" showing in particular how US subsidiaries outperform their competitors from other countries when the host country is Italy. Similarly, Wang, Clegg & Kafouros (2009)

demonstrate that the origin of MNEs investing in China has a varying effect in terms of

human capital, employment and technological engagement. Görg and Greenaway (2004)

argue that the origin of the MNE within the context of developed host economies can have a

significant effect on TFP. Based on this evidence, we investigate whether there is a MNEs

home-country nationality effect on regional productivity in the UK. The fourth hypothesis of

the paper is then formulated as:

H4: The impact of MNEs activities on regional productivity varies according to country of

origin of the parent company.

Analytical framework: Methodology and Measurement Issues

Methodology

8

In order to test the four hypotheses developed in the previous section, we first model Total Factor Productivity (TFP) in region j at time t as follows:

$$A_{it} \equiv TFP_{it} = f(HC_{it}, R_{it}, IA_{it}) \tag{1}$$

Equation (1) states that TFP in region j is a function of human capital (HC) in the region j and the following characteristics: R&D activity (R), and intangible assets (IA) of firms, located in region j. Based on the previous discussion, region's human capital interacts with firm characteristics facilitating a more effective absorption of knowledge spillovers from firms' activities. We specify a Cobb-Douglas regional production function with Parameter A to represent Hicks neutral technical change as follows:

$$Y_{it} = A_{it} L_{it}^{a} K_{it}^{1-a} \tag{2}$$

Y is value added in region j in year t, L is aggregate labour in region j, K is capital stock and a < 1 indicates the share of labour to value added. The only underlying assumption for (2) is the existence of constant returns to scale. In measuring TFP, we relax the assumption of perfect competition in the product market by adjusting labour and capital shares with cost mark-ups of monopolistic power. Re-arranging (2), we get a benchmark empirical expression for TFP:

$$A_{jt} \equiv TFP_{jt} = \frac{Y_{jt}}{L_{jt}^{a} K_{jt}^{1-a}}$$
 (3)

According to (3) TFP is a residual variable of value added minus weighted inputs. Once TFP is measured, it is modelled as a function of the determinants specified in (1) to formulate the following empirical specification:

$$TFP_{jt} = \alpha_0 + \alpha_1 HC_{jt} + \beta_1 \overline{R}_{jtMNE} + \beta_2 \overline{IA}_{jtMNE} + \beta_3 \overline{R}_{jtDOME} + \beta_4 \overline{IA}_{jtDOME} +$$

$$\gamma_1 \left(HC_{jt} \times \overline{R}_{jtMNE} \right) + \gamma_2 \left(HC_{jt} \times \overline{IA}_{jtMNE} \right)$$

$$+ \gamma_3 \left(HC_{jt} \times \overline{R}_{jtDOME} \right) + \gamma_4 \left(HC_{jt} \times \overline{IA}_{jtDOME} \right) + v_t + \eta_j + u_{jt}$$

$$(4)$$

the dependent variable is the level of TFP in region j and the right-hand side of the equation includes HC, \overline{R} and \overline{IA} , which are the average values of R&D and IAs of the MNE and DOME located in region j. The interaction terms within the parentheses measure absorptive capacity as per our previous discussion; parameters β capture the direct impact of each firm characteristic while parameters γ measure the effect of absorptive capacity on regional TFP. All variables are expressed in logs so as the estimated coefficients to represent elasticities, finally, specification (4) is augmented with year (v_i) and region (η_j) fixed effects to control for common macroeconomic effects and unobserved regional idiosyncrasies, respectively.

Measurement and Data Issues

Regional TFP Index

To estimate equation (4), we use data from two different sources. First, we gather data from regional accounts in the Office of National Statistics (ONS) to calculate TFP for 36 regions NUTS level 2 (Nomenclature of Territorial Units of Statistics) over the period 2004-2012. Second, we measure *R* and *IA* from FAME database (Bureau Van Dijk, 2012).

For the computation of TFP we use a superlative index number (Caves, Christensen & Diewert, 1982). The main advantage of this approach is that the underlying production function can take any flexible functional form The Cobb-Douglas function specified in (2) is the simplest form of production technology; nonetheless the superlative index number is a close linear approximation of other less restrictive functions such as the translog. We adjust TFP for the existence of market power as observed input shares are inaccurate when markets are imperfectly competitive. To account for imperfect competition, we adjust input shares to represent shares to total costs with the use of mark-ups (Appendix B and Table B1 shows the mark-up calculations for the 36 regions). We maintain the assumption of constant returns to scale following an influential line of research (Lucas & Rossi-Hansberg, 2002; Combes, Duranton & Gobillon, 2008), which hypothesizes that positive spillovers are external to the region itself so regions exhibit constant returns to scale to their own factor inputs, moreover we assume that MNEs impact on regional productivity in a Hicks–neutral way (i.e. all factors of production are affected symmetrically).

The superlative TFP index is specified in relative terms:

$$TFP_{jt} = \ln\left(\frac{Y_{jt}}{\overline{Y}_{t}}\right) - \tilde{a}_{jt}^{L} \ln\left(\frac{L_{jt}}{\overline{L}_{t}}\right) - (1 - \tilde{a}_{jt}^{L}) \ln\left(\frac{K_{jt}}{\overline{K}_{t}}\right)$$
(5)

Where Output Y is Value Added in region j, L is the number of employees ⁱⁱⁱ and K is capital stock. Variables with an upper bar denote reference points and defined as the geometric

average of the whole sample in year t. Labour share a is defined as the ratio of labour compensation to value added entering (5) in a Divisia share as: $a_{jt}^L = \frac{a_{jt} + \overline{a}_t}{2}$. Factor shares are allowed to vary across j and t, which is consistent with the existence of large time and region heterogeneity in the pattern of production. Factor share $a_{j,t}^L$ is adjusted for market power: $\tilde{a}_{jt}^L = \mu_j a_{jt}^L$, with μ to be the mark-up.

Data

Two samples of firms are constructed from FAME Database (2012), one for MNE subsidiaries and one for DOMEs. For MNEs, we use firms with at least one foreign shareholder that owns at least 50% of its capital adopting the definition of Guadalupe, Kuzmina & Thomas (2012). We thus restrict our analysis on majority and (or) wholly owned subsidiaries of foreign MNEs. This helps clearly delineating which firms are foreign owned and controlled even in cases of a low dispersion of shareholdings. It is well acknowledged (Chang, Chung & Moon, 2013) that different degrees of ownership are associated with a varying impact on industry, firm and market performance. An alternative broader definition of MNEs based on the degree of foreign control as well as on the dispersion of shares, which might highlight the impact of various entry modes (i.e. minority joint ventures becoming wholly owned subsidiaries) on regional TFP, is a task well beyond the scope of this paper. According to this criterion, the number of MNEs in the UK is found to be 11,057 for the period 2004-2012.

For DOMEs, we employed two selection criteria: first, the ultimate owner must be of domestic origin and own 50% (or above) of the corporation and second the DOMEs cannot be multinationals themselves. This is in order to strictly delineate the role of multinationality

¹ In Appendix C, Table C1 shows a full list of NUTS Level 2 regions.

per se-much in line with Castellani and Zanfei's (2006) and Frenz and Ietto-Gillies (2007) and thus creating a common selection criterion between the two groups of firms (i.e. full or majority ownership). We exclude from the group of DOMEs firms with a minority share to a foreign shareholder to maintain a strictly defined domestic ownership. With these adjustments, the number of DOMEs is found to be 16,548 for the sample period. As FAME data base is restricted to the sample of large and very large enterprises, the size of the representative firm in each group is expected to be similar. Table C1 in Appendix C displays the average firm size as measured either by the number of employees or the volume of sales for each group across regions. On average, DOMEs tend to be slightly larger if size is captured by the number of employees while MNEs tend to have larger volume of sales. This pattern is not universal as it varies across regions but it becomes evident that DOMEs and MNEs are of comparable size.

The two firm characteristics, R and IA are expressed in intensity forms as:

$$R_{ijt} = \frac{\text{R&D}_{ijt}}{\text{Sales}_{ijt}} \tag{6}$$

$$IA_{ijt} = \frac{\text{Intangible Assets}_{ijt}}{\text{Worker}_{iit}}$$
 (7)

where i indexes firm in region j at year t. Once we calculate these ratios for each firm in the MNE and DOME groups, we then calculate averages for each region j so as the analysis uses information for the average MNE and DOME in the region:

$$\overline{R}_{jt} = \frac{1}{C} \sum_{i=1}^{C} R_{ijt} \; ; \; \overline{IA}_{jt} = \frac{1}{C} \sum_{i=1}^{C} IA_{ijt}$$
 (8)

where C is the total number of firms for each group. To ensure that the average characteristics of MNEs and DOMEs are not driven by dominant firms in the region, we also compute weighted averages for R and IA denoted with an upper waved bar as:

$$\widetilde{R}_{jt} = \frac{1}{C} \sum_{i=1}^{C} \omega_{ijt} \frac{\text{R\&D}_{ijt}}{\text{Sales}_{ijt}} \; ; \; \widetilde{IA}_{jt} = \frac{1}{C} \sum_{i=1}^{C} \omega_{ijt} \frac{\text{Intangible Assets}_{ijt}}{\text{Worker}_{ijt}}$$
(9)

 ω is the share of each firm i to total sales in region j for each group. The baseline econometric specifications use the unweighted firm characteristics of (8). Table D3 IN Appendix D shows results for the weighted firm variables. Fig. A1 in Appendix A summarises definitions and data sources of all variables used in the paper.

Table C2 in Appendix C shows average values of exponential TFP indicating large cross-regional variation for 2004-2012. The group of regions with the highest level of TFP includes Inner London, Bedfordshire, Kent and Eastern Scotland while the group of regions at the bottom includes Staffordshire, East Anglia, East Yorkshire and Lancashire. Table C3 in Appendix C shows average values of \overline{R} and \overline{IA} for MNEs and DOMEs. Indicatively, MNEs maintain higher levels in both activities and it remains to be shown in the econometric analysis whether MNEs' superiority is critical for regional TFP.

Empirical Analysis and Results

Econometric Identification and Estimation

TFP in equation (4) is a residual measure implying a stationary data generation process. Nevertheless, the empirical regularity has shown that TFP might be persistent following AR(1) process:

$$\ln TFP_{it} = \rho \ln TFP_{it-1} + \beta \mathbf{X}_{it} + u_{it}$$
 (10)

with X to be an exogenous vector of covariates. To test the stationary properties of TFP, we run three different panel unit roots tests that rely on different assumptions about the evolution of the autoregressive parameter ρ . First, we apply the Levin, Lin & Chu, (2002) (LLC) test, which assumes that all regions have the same ρ . The alternative hypothesis is that ρ <1. Second, we run Im, Pesaran & Shin (2003) (IPS) that assumes panel heterogeneity with a null hypothesis $H_0: \rho_j = 1$, for each j versus the alternative that at least a fraction of crosssections is stationary. Last, the augmented Dickey-Fuller test (ADF) conducts individual panel unit root tests for each cross-section combining p-values to produce an overall test. The asymptotic properties of the three tests are suitable for a moderate-sized panel (T = 9, N = 36) like ours. Results from panel unit root tests are reported in Table 1.

[Table 1]

All three tests indicate rejecting the null hypothesis of a panel unit root providing robust evidence of a stationary TFP series. Given that TFP is an I(0) variable we then proceed with estimating equation (4) in levels without any further transformation.

Turning to the econometric estimation strategy there is a number of issues to be addressed before proceeding to estimation results. The main empirical question of the model is to test whether MNEs and DOMEs generate spillovers that boost regional TFP; this type of spillovers are not necessarily confined within regional borders, which implies the existence of cross-sectional (spatial) correlation $corr(u_{j_1}u_{k_1}) \neq 0$, region $j\neq k$ in the errors of specification (4). In this case, there are unobserved data dependencies that bias the error covariance matrix leading to inconsistent estimates concerning the true effect of \overline{R} and \overline{IA} on TFP.

In equation (4) there might be feedback effects between TFP and right-hand variables due to the tendency of R&D intensive MNEs and DOMEs to locate activities in regions with

high TFP in an attempt to benefit from local technological spillovers. Similarly, more productive regions tend to attract more skilled labour. Those considerations advocate for the use of the Generalized Methods of Moments (GMM) estimator that controls for potential endogeneity bias between TFP and firm characteristics. Another issue of concern in (4) is that fixed effects (η_j) essentially represent omitted variables that might also be correlated with other regressors and the error term. To address bias from omitted variables, we provide estimates from a dynamic panel estimator with one year lagged of the dependent variable on the right-hand side. To sum up, we control for cross-sectional dependence, endogeneity and omitted variables ensuring that our results are not driven from econometric bias.

We test for cross-sectional dependence (CD) using the test of Pesaran (2004). The CD test is a pair-wise correlation coefficient from OLS residuals ignoring cross-sectional dependence. The CD test rejects the null hypothesis of cross-sectional independence as shown in Table D1 in Appendix D. To control for cross-sectional dependence, we estimate (4) using the Common Correlated Pooled Effects Estimator (CCEP)^{vi} of Pesaran (2006) that augments the pooled OLS estimator with cross-sectional averages of both the dependent variable y and the vector of right-hand side variables \mathbf{X} to proxy for the linear combination of unobserved common effects. We gradually estimate (4) with CCEP in Table 2 using first a specification without interaction terms in column (1), a specification inclusive of interactions terms for absorptive capacity is shown in column (2).

Turning to GMM, a central issue is the use of appropriate instruments for the endogenous regressors. Valid instruments must be correlated with the endogenous variables while being uncorrelated with the error term in (4). We instrument endogenous variables with their lagged values in periods (t-2) and (t-3) based on the assumption that (4) has serially uncorrelated residuals. We run an Arrelano and Bond (AB) test for serial correlation for up to three lags without rejecting the null hypothesis of no-autocorrelation. Hansen(1982) -J and

Anderson LM test assess the identification of instruments. As shown at the bottom of Table 2 we cannot reject the null hypothesis of instrument validity while the null hypothesis of the LM test that the matrix of reduced-form coefficients in the first-stage regression is underidentified is rejected at high levels of significance. Therefore, we gather enough evidence that higher order lags of the endogenous variables are valid instruments. The GMM estimation adopts the extension of Chudik and Pesaran (2015) by including lags of cross-section averages in both first and second stage equations in order to control for cross-sectional dependence. GMM estimates with and without interaction terms are shown in columns (3) and (4). Finally, as far as the dynamic panel estimator is concerned, the Least Squared Dummy Variables (LSDV) estimator with a lagged dependent variable (TFP_{t-1}) among the regressors generates bias of the order 1/T, where T is the number of years in the panel (Nickell, 1981). Judson and Owen (1999) show that the appropriateness of the dynamic panel estimator depends on the data under use. Accordingly, the corrected LSDV (LSDVC) estimator of Kiviet (1995) outperforms all alternative estimators in terms of efficiency gains for panels with a modest number of years (T=9) and a large number of cross-sections (N=36). Table 2 shows results from CCEP, GMM and LSDVC estimators.

[Table 2]

Discussion of Results and Further Robustness Analysis

The coefficient of TFP_{t-1} in LSDVC estimations is positive and statistically significant, as expected. Regarding H1, the autonomous coefficient of R&D intensity, \overline{R}_{MNE} , is positive and statistically significant in CCEP and GMM specifications in columns (1) and (3). On the other hand, the autonomous coefficient of \overline{R}_{DOME} is insignificant. These results provide support for H1 about the relatively stronger impact of MNEs' R&D on regional TFP. The positive effect of MNEs' R&D is robust to alternative estimation techniques that control for

cross-regional correlation and endogeneity bias. The highest elasticity value of regional TFP with respect to R&D of MNEs is in LSDVC, 5.2% while it is 2.7% and 1.7% in CCEP and GMM, respectively. These numbers are interpreted as follows: a 2.7% increase in TFP is achieved after a 100% increase in R&D intensity of MNEs while the effect is almost doubled when specification (4) is estimated with LSDVC. Although this effect is small in absolute economic terms, our finding is in line with Barrios, Görg, & Strobl (2003) and Cantwell and Mudambi (2005) about the relative R&D strength of MNEs.

The estimates of intangibles \overline{IA}_{MNE} indicate that MNEs specific Oas are important in enhancing regional productivity while the coefficient of \overline{IA}_{DOME} is either insignificant or when significant is negative. The economic effect of \overline{IA}_{MNE} in regional productivity is relatively smaller than the one of \overline{R}_{MNE} found in H1. The elasticity of regional TFP with respect to \overline{IA}_{MNE} is between 1.1% and 1.6% across the three different estimators. The pattern of our results provides support to H2 and it is compatible to Kramer et al., (2011), underlining the superiority of MNEs' organizational and managerial practices in promoting local development.

With regard to H3 the quality of human capital in a region improves directly TFP with the effect to lie between 5% and 72%. Our results signify the importance of human capital in boosting productivity. The magnitudes of the HC coefficients found in our paper are close to firm level evidence (Moretti, 2004) about the effect of human capital on TFP while they are relatively higher than country level evidence (Milner & Upadhyay, 2000). Regarding the role of human capital in improving absorptive capacity, we do notice that the interaction terms of HC with the four firm specific characteristics in CCEP and LSDVC estimations are positive and statistically significant with the exception of $HC \times \overline{IA}_{DOME}$. All interaction terms become positive and statistically significant in the GMM estimation. In the CCEP estimation, the elasticity of TFP with respect to absorptive capacity is higher when the focus is on MNEs'

characteristics, 19.4% and 25.1% for \overline{R}_{MNE} and \overline{IA}_{MNE} , respectively. A qualitatively similar pattern holds in the LSDVC results. Absorptive capacity with respect to \overline{R}_{DOME} and \overline{IA}_{DOME} in GMM suggests that regions with higher level of human capital increase TFP from \overline{R}_{DOME} related spillovers by 6% more than regions with less human capital. Overall, our results support the hypothesis that human capital is the necessary condition in order regions to capitalize on sophisticated inputs that MNEs and DOMEs provide with their presence in the local economy. A similar effect of complementarity between local characteristics and FDI is also found for Spanish regions in López-Bazo et al. (2006).

Human capital is a regional characteristic that plays a crucial role in region's sustainable development as it provides these capabilities that a firm can use to produce new product and(or) process innovations (Faggian & McCann, 2009). This kind of interactive exchange of skills and knowledge between regions and firms can be viewed as a factor that fosters the degree of embeddedness of both MNEs and DOMEs with local economies (Kramer, et al., 2011). Phelps, Mackinnon, Stone, & Braidford (2003) find that the availability of labour skills in Wales and North East of England is the main determinant of MNEs' location decisions. Our results also support the notion that productivity gains from the innovative activities of MNEs are multiple if local regions are well endowed in highly educated workers. Similarly, R&D activity of DOMEs becomes beneficial for regional TFP if local economies have the necessary level of absorptive capacity to transfer these capabilities into tangible productivity gains. Finally, our analysis finds regional productivity gains from the interaction of HC with \overline{IA}_{DOME} to be significant only in the GMM specification while the economic size of the interaction term is the smallest reflecting mainly the low level of investment on IAs in DOMEs, which makes this group of firms to be less important in the development process of regions. vii

A further test of robustness is to use a more basic TFP index instead of the one specified in (6) with hypothetical reference points and mark-ups. This TFP index has the benefit of minimizing measurement errors that may be present in market power estimates. For this sensitivity test, we replicate CCEP and LSDVC estimators for the unweighted TFP as the dependent variable (See Table D2 in Appendix D). The qualitative pattern of the results is unchanged, TFP has an elasticity of 1.8% and 1.6% with respect to \overline{R}_{MNE} while the coefficient of \overline{IA}_{MNE} is similar to the estimate displayed in Table 2. TFP gains from R&D and IAs of MNEs are analogous to the level of absorptive capacity in the region. The only noticeable difference between Table 2 and Table D2 is in interaction terms $HC \times \overline{R}_{DOME}$ and $HC \times \overline{IA}_{DOME}$, which remain statistically insignificant. The last test of robustness is to estimate (4) with weighted firm characteristics as defined in (9). Results from this specification are shown in Table D3 in Appendix D. Concerning the impact of HC and R_{MNE} , estimates remain highly statistically significant with the estimated coefficient of \widetilde{R}_{MNE} to be larger in all specifications than the unweighted one \overline{R}_{MNF} . The main difference between specifications with weighted and unweighted firm characteristics is that the impact of IA_{MNE} turns insignificant while the impact of \widetilde{R}_{DOME} is found positive and statistically significant in two out of the six specifications. Interestingly, the impact of \widetilde{IA}_{MNE} remains significant even after being interacted with human capital while the effect of \widetilde{R}_{DOME} increases with higher levels of human capital in the region, an effect that is also evident in specifications with the unweighted firms' characteristics. Overall, our results are robust to controlling for various sources of econometric bias and the adoption of two different types of TFP (one with mark ups and one without) and raise no doubt about the support they provide to our hypotheses H1 and H3. The use of weighted firm characteristics casts some doubt for the validity of H2 implying that estimates of \overline{IA}_{MNE} in Table 2 are mainly driven by IAs of dominant large

MNEs in the region. The role of IAs in regional productivity can be a path of future research with specific information about the different components that comprise of the current aggregate measure of intangibles assets.

Origins of MNEs and Regional TFP

Given that we combine regional with firm level data, we can investigate whether the nationality of MNEs matters for regional TFP. To this end, we distinguish among different origins of foreignness (Frenz & Ietto-Gillies, 2007) splitting the group of MNEs into four geographical sub-groups, namely to those with headquarters in EU, USA, Japan and the rest of the world (ROW). Then, we estimate using GMM a variant of specification (4) where \overline{R}_{MNE} is decomposed into \overline{R}_{EU} , \overline{R}_{USA} , \overline{R}_{Japan} , \overline{R}_{ROW} and IA_{MNE} into \overline{IA}_{EU} , \overline{IA}_{USA} , \overline{IA}_{Japan} , \overline{IA}_{ROW} . Results are reported in two columns in Table 3, one only with level variables and one with all interaction terms inclusive. Contrary to previous studies (Bloom, Sadun & Van Reenen, 2012), we find that the R&D of European and Japanese MNEs' have a stronger impact on UK regional TFP. The negative coefficient of \overline{R}_{ROW} in Table 3 indicates the differentiating impact of 'systems of origin' on regional productivity. The opposite signs of \overline{R}_{DOME} and \overline{R}_{ROW} suggest that the impact of DOMEs on TFP can sometimes be more crucial than those of MNEs (Altomonte & Pennings, 2009). Our results regarding R&D activity of MNEs from specific origins signify the negative foreignness effect whereby domestic MNEs occasionally outperform foreign subsidiaries (Higón & Antolin, 2012).

Turning to IAs, it is only *IAusa* that has a positive impact on regional TFP with IAs of MNEs from other origins to be either negative or insignificant. Looking at the interaction terms in column (2), TFP gains are multiplied when R&D activity of EU and Japan MNEs and IAs of USA MNEs are interacted with human capital. These positive interaction terms indicate that the dynamic relationship between host-county location advantage such as HC

and Oas from specific origins can further enhance location assets of the host-economy leading to further regional productivity improvements (Makino, Beamish & Zhao, 2002; Hennart, 2009). Evidence from Table 3 is also compatible to Iammarino, Piva, Vivarelli, & Von Tunzelmann (2012) and Park (2015) on how the interplay between MNEs characteristics from specific origins and local capabilities can make regions more competitive. To conclude, when we disintegrate the activities of MNEs we find heterogeneous effects, which also support that DOMEs can outperform subsidiaries from certain "systems of origin" (Cantwell & Iammarino, 2000; Ke & Lai, 2011).

[Table 3]

Conclusion and Policy Implications

We have investigated the relative impact of MNEs and DOMEs on regional productivity in the UK. The analysis made use of firm level data on R&D and intangible assets. Descriptive evidence showed that MNEs have higher levels of intensity in R&D and intangibles compared to DOMEs. The econometric results confirmed that the impact of R&D of MNEs on regional TFP outperforms that of DOMEs. Regarding the effect of IAs from MNEs, this is positive when we use unweighted firm characteristics but when the sales share of each MNE in the region is taken into account then the effect of IAs per worker becomes negligible. Additionally, there are modifications in the pattern of the results when the *origin of foreignness* of MNEs is taken into account, in which case we find evidence that DOMEs can outperform MNEs from specific regions. This evidence indicates that although the collective impact of MNEs is vital on regional TFP, R&D performance of DOMEs can be economically more significant than R&D of MNEs from specific geographical areas. Therefore, in the

regional context of a developed country, the role of DOMEs should be regarded as important as the role of MNEs in understanding the puzzle of regional productivity. There are two possible explanations for that: firstly, laggard regions can more easily absorb the organisational expertise of DOMEs, which is on average below the standards of the managerial and organisational know-how of MNEs. Secondly, the asymmetric effects from the country of origin specifications suggest that MNEs reflect the characteristics of their home countries which can impact on their decisions and strategies in a way that may not be always aligned to the needs of the host regions.

This poses a major challenge for the design and the implementation of regional inward investment policies as they should be more targeted and more fine-tuned and selective. In particular, policy makers should seek to leverage effectively gains from global integration through smart, selective and DOME-compatible participation in global value chains and MNE production systems. Existing regional policies should thus depart from viewing regions as border-bounded territories to more global—networked geographical entities and aim to identify ways in which they can strategically engage with these. This requires focus on and analysis of specific MNEs strategies and their degree of embeddedness so as to devise and implement tailor-made regional policies that optimise the joint advantages of MNEs and DOMEs.

Our research provides many opportunities for further research. These include comparing the role of MNEs from developed and emerging economies and an exploration of the combined effect of MNEs and DOMEs on regional productivity. The role of developmental industrial policies could also be incorporated in future analysis. That said we have unearthed a number of interesting, more nuanced and underexplored relationships that we feel, have added value to this very important issue.

Acknowledgements: We would like to thank participants of: RSA Winter Conference, London 2015; the Fifth Reading-UNCTAD International Business Conference at the University of Reading's Henley Business School, 2015; 15th Annual ETSG conference at the University of Birmingham. We are also grateful to Michela Vecchi and three anonymous referees for comments and suggestions on earlier versions of the paper. The usual disclaimer applies.

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APPENDICES

Appendix A

Figure A1: Definition of Variables

Name	Definition
Regional TFP	2 4
Output (Y)	Gross Value Added (GVA) expressed in 1995 GBP constant prices, using production price indices (PPI), Office of National Statistics (ONS), Regional Accounts.
Labour (L) Capital Stock (K)	Number of employees, ONS. K is is generated from the perpetual inventory method: $K_{jt} = K_{jt-1} - \delta K_{jt-1} + I_{jt-1}$, where δ is the
Initial Capital Stock (K_0)	physical depreciation rate, defined at the constant rate of 10% for all j . $K_{j2000} \equiv \frac{I_{j2000}}{g_j + \delta}$, where g is the average growth rate
Investment (I)	of region <i>j</i> 's investment over the sample period and subscript 2000 indicates the first year with investment data available. Gross Fixed Capital Formation (GFCF) expressed in 1995 GBP constant prices using Capital price index, ONS.
Labour share (a)	Labour compensation ratio to GVA, labour compensation expressed in 1995 GBP constant prices using ULC indices takes from OECD-STAN (2010).
Human Capital (HC)	Percentage of Persons with a Degree from Tertiary Education (Levels 5-8) to Total Labour Force (ONS).
Firm Level Data-FAME	
R&D (R)	R&D expenditures in current GBP includes costs related to the evaluation and adoption of new technology, cost incurred on development projects such as design and testing of new or improved products.
Sales Intangibles (IA)	Total Turnover in current GBP. Intangible Assets in current GBP include expenditures in: (a) Patents, trademarks and licenses, (b) technology and content and (c) contractual relationships such as cost on customer loyalty and customer portfolio.
Employees	Number of Employees.

Appendix B

The Calculation of Mark-ups

The methodological novelty of the Roeger (1995) in calculating mark-ups is associated with the combination of production and cost based Solow Residual (SR), which eliminate unobserved productivity shocks. After eliminating unobserved productivity shocks we obtain unbiased measures of market power in the region thus more accurate regional TFP measures. The SR is defined in differences of growth rates of output and production inputs as follows:

$$SR = \frac{\Delta Y_{jt}}{Y_{jt}} - a \frac{\Delta L_{jt}}{L_{jt}} - (1 - a) \frac{\Delta K_{jt}}{K_{jt}} = B \left(\frac{\Delta Y_{jt}}{Y_{jt}} - \frac{\Delta K_{jt}}{K_{jt}} \right) + (1 - B) \frac{\Delta \theta_{jt}}{\theta_{jt}}$$
(B1)

where j and t denote regions and time, respectively and θ refers to unobservable technical progress, also specified in growth rates. The definition of the remaining variables in (B1) is the same as per our production function in equation (2) in the text. The first side of (B1) is equivalent to the growth rate of SR (equivalently a measure of TFP growth) with a being the labour share (wages to value added) in a production function with constant returns to scale. In the presence of perfect competition, B=0 the right-hand side of (B1) is eliminated hence SR is identical to technical progress. This is the so-called "invariance" property of the SR (Hall, 1990) that is not often observed in reality as the residual tends to be higher in expansions and lower in recessions. The reason for this is that the underlying assumption of perfect competition in (B1) does not hold.

Roeger (1995) derives unbiased estimates for the degree of market power using a dual productivity SR measure with cost rather than revenue data as follows:

$$CSR \equiv a \frac{\Delta w_{jt}}{w_{jt}} + \left(1 - a\right) \frac{\Delta r_{jt}}{r_{jt}} - \frac{\Delta p_{jt}}{p_{jt}} = -B \left(\frac{\Delta p_{jt}}{p_{jt}} - \frac{\Delta r_{jt}}{r_{jt}}\right) + \left(1 - B\right) \frac{\Delta \theta_{jt}}{\theta_{jt}}$$
(B2)

where w is the wage rate and r is the cost price for the use of capital stock in region j. Subtracting equation (B2) from (B1) and re-arranging we obtain:

$$\left(\frac{\Delta Y_{jt}}{Y_{jt}} + \frac{\Delta p_{jt}}{p_{jt}}\right) - a_{jt} \left(\frac{\Delta L_{jt}}{L_{jt}} + \frac{\Delta w_{jt}}{w_{jt}}\right) - (1 - a_{jt}) \left(\frac{\Delta K_{jt}}{K_{jt}} + \frac{\Delta r_{jt}}{r_{jt}}\right) = \left(\frac{\Delta Y_{jt}}{Y_{jt}} + \frac{\Delta p_{jt}}{p_{jt}}\right) - \left(\frac{\Delta K_{jt}}{K_{jt}} + \frac{\Delta r_{jt}}{r_{jt}}\right)$$
(B3)

After writing (B3) more compactly with a stochastic error term ε we get:

$$\Delta y_{it} = \mu_i \Delta x_{it} + \varepsilon_{it} \tag{B4}$$

Where μ in each individual region j calculated from a cost based SR (CSR). Essentially, the left hand side of (B3) is a nominal SR while the right hand side represents the growth rate of nominal output per capital. B4 group together price and volume terms so as allowing an estimate of μ with only observable variables. This means that Δy is measured as the difference between growth rates in value added and the adjusted growth rates of labour and capital. Δx is the growth rate of nominal output per capital. Parameter a is the observed share of labour compensation to value added. The estimated values of μ from (B4) are used to adjust labour shares in equation (5). Estimates of mark-ups for each region are shown below.

TABLE B1: Mark-Up Estimates for NUTS 2UK regions, 2004-2012

NUTS2	Mark-Up
UKC1	1.189
UKC2	1.062
UKD1	0.700
UKD3	0.740
UKD4	1.164
UKD6	1.304
UKD7	1.025
UKE1	1.143
UKE2	1.340
UKE3	0.735
UKE4	1.204
UKF1	1.674
UKF2	1.257
UKF3	1.449
UKG1	1.906
UKG2	1.903
UKG3	1.021
UKH1	1.130
UKH2	1.235
UKH3	1.006
UKI1	1.112
UKI2	1.782
UKJ1	1.226
UKJ2	1.219
UKJ3	1.323
UKJ4	1.559
UKK1	1.159
UKK2	1.117
UKK3	1.189
UKK4	1.131
UKL1	1.339
UKL2	1.150
UKM2	1.231
UKM3	0.778
UKM5	0.983
UKM6	1.119
Average	1.211

Appendix C

TABLE C1: Average Firm Size of DOMEs and MNEs across UK Regions

TABLE C1: Average Firm Size of DOM				
Region	Employ		Sales (in 00	
	DOMEs	MNEs	DOMEs	MNEs
Tees Valley and Durham	197	241	28,938	48,716
Northumberland and Tyne and Wear	189	183	30,858	32,935
Cumbria	123	103	19,119	16,038
Greater Manchester	213	170	28,609	39,375
Lancashire	207	173	26,414	26,428
Cheshire	260	288	50,474	45,428
Merseyside	215	296	34,481	61,822
East Yorkshire and Northern	249	194	32,852	50,179
Lincolnshire	249	194	32,632	30,179
North Yorkshire	171	222	25,203	48,508
South Yorkshire	236	182	34,217	31,048
West Yorkshire	212	168	74,710	34,003
Derbyshire and Nottinghamshire	324	385	51,586	62,539
Leicestershire, Rutland and	301	245	46,098	53,509
Northamptonshire	301	243	40,096	33,309
Lincolnshire	288	242	59,107	36,672
Hereford, Worcestershire and	291	326	44,952	64,981
Warwickshire			,	ŕ
Shrophire and Staffordshire	367	319	49,659	47,849
West Midlands	259	186	31,524	43,450
East Anglia	299	172	31,489	35,636
Bedfordshire and Hertfordshire	340	242	52,720	56,502
Essex	247	262	45,050	63,854
Inner London	367	261	70,103	123,662
Outer London	383	178	53,048	50,652
Berkshire, Buckinghamshire and	282	265	73,026	64,719
Oxfordshire			,	•
Surrey, East and West Sussex	311	257	36,287	107,898
Hampshire and Isle of Wight	248	348	39,376	107,429
Kent	295	263	48,420	62,868
Gloucestershire, Wiltshire and Bristol/Bath area	263	233	32,125	51,732
Dorset and Somerset	324	196	25,704	32,605
Cornwall and Isles of Scilly	116	118	28,013	25,956
Devon	219	124	33,678	17,959
West Wales and The Valleys	98	160	18,160	29,404
East Wales	181	216	31,507	49,730
East wates Eastern Scotland	271	220	49,335	33,634
South Western Scotland	245	236	33,225	61,847
North Eastern Scotland	243 252	188	28,253	27,638
Highlands and Islands	192	270	21,334	27,590
Mean	251	225	51,767	84,329

TABLE C2: Mean Values of TFP for UK Regions (NUTS Level 2), 2004-2012

NUTS 2	Nalues of TFP for UK Regions (NUTS Level 2), 2004-2012 Region	exp(TFP)
UKC1	Tees Valley and Durham	2.16
UKC2	Northumberland and Tyne and Wear	2.04
UKD1	Cumbria	1.89
UKD3	Greater Manchester	2.15
UKD4	Lancashire	1.64
UKD6	Cheshire	1.84
UKD7	Merseyside	1.98
UKE1	East Yorkshire and Northern Lincolnshire	1.64
UKE2	North Yorkshire	1.86
UKE3	South Yorkshire	2.11
UKE4	West Yorkshire	1.93
UKF1	Derbyshire and Nottinghamshire	2.08
UKF2	Leicestershire, Rutland and Northamptonshire	1.87
UKF3	Lincolnshire	1.98
UKG1	Hereford, Worcestershire and Warwickshire	2.37
UKG2	Shrophire and Staffordshire	1.58
UKG3	West Midlands	2.10
UKH1	East Anglia	1.61
UKH2	Bedfordshire and Hertfordshire	2.30
UKH3	Essex	1.84
UKI1	Inner London	2.37
UKI2	Outer London	1.95
UKJ1	Berkshire, Buckinghamshire and Oxfordshire	2.24
UKJ2	Surrey, East and West Sussex	1.95
UKJ3	Hampshire and Isle of Wight	1.94
UKJ4	Kent	2.16
UKK1	Gloucestershire, Wiltshire and Bristol/Bath area	1.80
UKK2	Dorset and Somerset	1.96
UKK3	Cornwall and Isles of Scilly	1.65
UKK4	Devon	2.04
UKL1	West Wales and The Valleys	1.83
UKL2	East Wales	2.03
UKM2	Eastern Scotland	2.23
UKM3	South Western Scotland	1.96
UKM5	North Eastern Scotland	2.26
UKM6	Highlands and Islands	1.82
Mean		1.98

TABLE C3: Average Values of R&D and Intangibles of MNEs and DOMEs in the UK, 2004-2012

Tees Valley and Durham	2004 2012				
Tees Valley and Durham Northumberland and Tyne and Wear Cumbria 1.5% 10.3 2.3% Greater Manchester 1.3% 80.4 2.2% Lancashire 0.6% 99.9 0.5% 1 Cheshire 7.4% 36.9 0.1% Merseyside 0.1% 255.8 0.01% 1 East Yorkshire and Northern Lincolnshire North Yorkshire South Yorkshire 0.6% 98.2 0.1% South Yorkshire 0.4% 65.2 0.03% West Yorkshire 0.2% 40.7 0.1% Derbyshire and Nottinghamshire 1.1% 90.1 0.1% Leicestershire, Rutland and Northamptonshire Lincolnshire 1.6% 34.6 0.1% Hereford, Worcestershire and Warwickshire 0.8% 49.4 0.6% West Midlands 0.3% 149.6 0.2% East Anglia Pedfordshire and Hertfordshire 4.1% 110.4 0.3% 3 Essex 3.3% 34.3 0.1% Inner London 0.2% 198.4 0.04% 1 Outer London 0.8% 109.1 0.03% Berkshire, Buckinghamshire and Oxfordshire 1.6% 161.4 2.4% 3 Surrey, East and West Sussex 1.2% 114.2 0.3% 2	NUTS2	$\overline{R}_{\scriptscriptstyle MNE}$	\overline{IA}_{MNE}	$\overline{R}_{\scriptscriptstyle DOME}$	\overline{IA}_{DOME}
Cumbria 1.5% 10.3 2.3% Greater Manchester 1.3% 80.4 2.2% Lancashire 0.6% 99.9 0.5% 1 Cheshire 7.4% 36.9 0.1% Merseyside 0.1% 255.8 0.01% 1 East Yorkshire and Northern Lincolnshire 0.7% 36.1 0.1% North Yorkshire 0.6% 98.2 0.1% South Yorkshire 0.4% 65.2 0.03% West Yorkshire 0.2% 40.7 0.1% Derbyshire and Nottinghamshire 1.1% 369.5 0.2% Leicestershire, Rutland and Northamptonshire 1.1% 369.5 0.2% Lincolnshire 1.6% 34.6 0.1% Hereford, Worcestershire and Warwickshire 0.2% 155.6 1.0% Shrophire and Staffordshire 0.8% 49.4 0.6% West Midlands 0.3% 149.6 0.2% East Anglia 9.1% 72.1 1.4% Bedfordshire an	Tees Valley and Durham		48.3	0.01%	1.8
Care Care	Northumberland and Tyne and Wear	1.1%	54.7	0.2%	1.7
Lancashire	Cumbria	1.5%	10.3	2.3%	2.9
Cheshire 7.4% 36.9 0.1% Merseyside 0.1% 255.8 0.01% 1 East Yorkshire and Northern Lincolnshire 0.7% 36.1 0.1% North Yorkshire 0.6% 98.2 0.1% South Yorkshire 0.4% 65.2 0.03% West Yorkshire 0.2% 40.7 0.1% Derbyshire and Nottinghamshire 1.1% 90.1 0.1% Leicestershire, Rutland and Northamptonshire 1.1% 369.5 0.2% Lincolnshire 1.6% 34.6 0.1% Hereford, Worcestershire and Warwickshire 0.2% 155.6 1.0% Shrophire and Staffordshire 0.8% 49.4 0.6% West Midlands 0.3% 149.6 0.2% East Anglia 9.1% 72.1 1.4% Bedfordshire and Hertfordshire 4.1% 110.4 0.3% 3 Essex 3.3% 34.3 0.1% 1 Lincolnshire 4.1% 110.4 0.3% 3 East Anglia 9.1% 72.1 1.4% 0.1%<	Greater Manchester	1.3%	80.4	2.2%	4.0
Merseyside 0.1% 255.8 0.01% 1 East Yorkshire and Northern Lincolnshire 0.7% 36.1 0.1% 0.1% North Yorkshire 0.6% 98.2 0.1% South Yorkshire 0.4% 65.2 0.03% West Yorkshire 0.2% 40.7 0.1% Derbyshire and Nottinghamshire 1.1% 90.1 0.1% Leicestershire, Rutland and Northamptonshire 1.1% 369.5 0.2% Lincolnshire 1.6% 34.6 0.1% Hereford, Worcestershire and Warwickshire 0.2% 155.6 1.0% Shrophire and Staffordshire 0.8% 49.4 0.6% West Midlands 0.3% 149.6 0.2% East Anglia 9.1% 72.1 1.4% Bedfordshire and Hertfordshire 4.1% 110.4 0.3% 3 Essex 3.3% 34.3 0.1% Inner London 0.2% 198.4 0.04% 1 Outer London 0.8% 109.1 0.03% Berkshire, Buckinghamshire and Oxfordshire 1.6% 161.	Lancashire	0.6%	99.9	0.5%	12.0
East Yorkshire and Northern Lincolnshire 0.7% 36.1 0.1% North Yorkshire 0.6% 98.2 0.1% South Yorkshire 0.4% 65.2 0.03% West Yorkshire 0.2% 40.7 0.1% Derbyshire and Nottinghamshire 1.1% 90.1 0.1% Leicestershire, Rutland and Northamptonshire 1.1% 369.5 0.2% Lincolnshire 1.6% 34.6 0.1% Hereford, Worcestershire and Warwickshire 0.2% 155.6 1.0% Shrophire and Staffordshire 0.8% 49.4 0.6% West Midlands 0.3% 149.6 0.2% East Anglia 9.1% 72.1 1.4% Bedfordshire and Hertfordshire 4.1% 110.4 0.3% 3 Essex 3.3% 34.3 0.1% Inner London 0.2% 198.4 0.04% 1 Outer London 0.8% 109.1 0.03% Berkshire, Buckinghamshire and Oxfordshire 1.6% 161.4 2.4% 3 Surrey, East and West Sussex 1.2% 114.2 </td <td>Cheshire</td> <td>7.4%</td> <td>36.9</td> <td>0.1%</td> <td>7.0</td>	Cheshire	7.4%	36.9	0.1%	7.0
North Yorkshire 0.6% 98.2 0.1% South Yorkshire 0.4% 65.2 0.03% West Yorkshire 0.2% 40.7 0.1% Derbyshire and Nottinghamshire 1.1% 90.1 0.1% Leicestershire, Rutland and Northamptonshire 1.1% 369.5 0.2% Lincolnshire 1.6% 34.6 0.1% Hereford, Worcestershire and Warwickshire 0.2% 155.6 1.0% Shrophire and Staffordshire 0.8% 49.4 0.6% West Midlands 0.3% 149.6 0.2% East Anglia 9.1% 72.1 1.4% Bedfordshire and Hertfordshire 4.1% 110.4 0.3% 3 Essex 3.3% 34.3 0.1% Inner London 0.2% 198.4 0.04% 1 Outer London 0.8% 109.1 0.03% Berkshire, Buckinghamshire and Oxfordshire 1.6% 161.4 2.4% 3 Surrey, East and West Sussex 1.2% 114.2 <	Merseyside	0.1%	255.8	0.01%	11.8
South Yorkshire 0.4% 65.2 0.03% West Yorkshire 0.2% 40.7 0.1% Derbyshire and Nottinghamshire 1.1% 90.1 0.1% Leicestershire, Rutland and Northamptonshire 1.1% 369.5 0.2% Lincolnshire 1.6% 34.6 0.1% Hereford, Worcestershire and Warwickshire 0.2% 155.6 1.0% Shrophire and Staffordshire 0.8% 49.4 0.6% West Midlands 0.3% 149.6 0.2% East Anglia 9.1% 72.1 1.4% Bedfordshire and Hertfordshire 4.1% 110.4 0.3% 3 Essex 3.3% 34.3 0.1% Inner London 0.2% 198.4 0.04% 1 Outer London 0.8% 109.1 0.03% Berkshire, Buckinghamshire and Oxfordshire 1.6% 161.4 2.4% 3 Surrey, East and West Sussex 1.2% 114.2 0.3% 2	East Yorkshire and Northern Lincolnshire	0.7%	36.1	0.1%	4.2
West Yorkshire 0.2% 40.7 0.1% Derbyshire and Nottinghamshire 1.1% 90.1 0.1% Leicestershire, Rutland and Northamptonshire 1.1% 369.5 0.2% Lincolnshire 1.6% 34.6 0.1% Hereford, Worcestershire and Warwickshire 0.2% 155.6 1.0% Shrophire and Staffordshire 0.8% 49.4 0.6% West Midlands 0.3% 149.6 0.2% East Anglia 9.1% 72.1 1.4% Bedfordshire and Hertfordshire 4.1% 110.4 0.3% 3 Essex 3.3% 34.3 0.1% Inner London 0.2% 198.4 0.04% 1 Outer London 0.8% 109.1 0.03% Berkshire, Buckinghamshire and Oxfordshire 1.6% 161.4 2.4% 3 Surrey, East and West Sussex 1.2% 114.2 0.3% 2	North Yorkshire	0.6%	98.2	0.1%	2.3
Derbyshire and Nottinghamshire 1.1% 90.1 0.1% Leicestershire, Rutland and Northamptonshire 1.1% 369.5 0.2% Lincolnshire 1.6% 34.6 0.1% Hereford, Worcestershire and Warwickshire 0.2% 155.6 1.0% Shrophire and Staffordshire 0.8% 49.4 0.6% West Midlands 0.3% 149.6 0.2% East Anglia 9.1% 72.1 1.4% Bedfordshire and Hertfordshire 4.1% 110.4 0.3% 3 Essex 3.3% 34.3 0.1% Inner London 0.2% 198.4 0.04% 1 Outer London 0.8% 109.1 0.03% Berkshire, Buckinghamshire and Oxfordshire 1.6% 161.4 2.4% 3 Surrey, East and West Sussex 1.2% 114.2 0.3% 2	South Yorkshire	0.4%	65.2	0.03%	1.5
Leicestershire, Rutland and Northamptonshire 1.1% 369.5 0.2% Lincolnshire 1.6% 34.6 0.1% Hereford, Worcestershire and Warwickshire 0.2% 155.6 1.0% Shrophire and Staffordshire 0.8% 49.4 0.6% West Midlands 0.3% 149.6 0.2% East Anglia 9.1% 72.1 1.4% Bedfordshire and Hertfordshire 4.1% 110.4 0.3% 3 Essex 3.3% 34.3 0.1% Inner London 0.2% 198.4 0.04% 1 Outer London 0.8% 109.1 0.03% Berkshire, Buckinghamshire and Oxfordshire 1.6% 161.4 2.4% 3 Surrey, East and West Sussex 1.2% 114.2 0.3% 2	West Yorkshire	0.2%	40.7	0.1%	7.1
Lincolnshire 1.6% 34.6 0.1% Hereford, Worcestershire and Warwickshire 0.2% 155.6 1.0% Shrophire and Staffordshire 0.8% 49.4 0.6% West Midlands 0.3% 149.6 0.2% East Anglia 9.1% 72.1 1.4% Bedfordshire and Hertfordshire 4.1% 110.4 0.3% 3 Essex 3.3% 34.3 0.1% Inner London 0.2% 198.4 0.04% 1 Outer London 0.8% 109.1 0.03% Berkshire, Buckinghamshire and Oxfordshire 1.6% 161.4 2.4% 3 Surrey, East and West Sussex 1.2% 114.2 0.3% 2	Derbyshire and Nottinghamshire	1.1%	90.1	0.1%	6.1
Hereford, Worcestershire and Warwickshire 0.2% 155.6 1.0% Shrophire and Staffordshire 0.8% 49.4 0.6% West Midlands 0.3% 149.6 0.2% East Anglia 9.1% 72.1 1.4% Bedfordshire and Hertfordshire 4.1% 110.4 0.3% 3 Essex 3.3% 34.3 0.1% Inner London 0.2% 198.4 0.04% 1 Outer London 0.8% 109.1 0.03% Berkshire, Buckinghamshire and Oxfordshire 1.6% 161.4 2.4% 3 Surrey, East and West Sussex 1.2% 114.2 0.3% 2	Leicestershire, Rutland and Northamptonshire	1.1%	369.5	0.2%	2.4
Shrophire and Staffordshire 0.8% 49.4 0.6% West Midlands 0.3% 149.6 0.2% East Anglia 9.1% 72.1 1.4% Bedfordshire and Hertfordshire 4.1% 110.4 0.3% 3 Essex 3.3% 34.3 0.1% Inner London 0.2% 198.4 0.04% 1 Outer London 0.8% 109.1 0.03% Berkshire, Buckinghamshire and Oxfordshire 1.6% 161.4 2.4% 3 Surrey, East and West Sussex 1.2% 114.2 0.3% 2	Lincolnshire	1.6%	34.6	0.1%	1.0
West Midlands 0.3% 149.6 0.2% East Anglia 9.1% 72.1 1.4% Bedfordshire and Hertfordshire 4.1% 110.4 0.3% 3 Essex 3.3% 34.3 0.1% Inner London 0.2% 198.4 0.04% 1 Outer London 0.8% 109.1 0.03% Berkshire, Buckinghamshire and Oxfordshire 1.6% 161.4 2.4% 3 Surrey, East and West Sussex 1.2% 114.2 0.3% 2	Hereford, Worcestershire and Warwickshire	0.2%	155.6	1.0%	1.6
East Anglia 9.1% 72.1 1.4% Bedfordshire and Hertfordshire 4.1% 110.4 0.3% 3 Essex 3.3% 34.3 0.1% Inner London 0.2% 198.4 0.04% 1 Outer London 0.8% 109.1 0.03% Berkshire, Buckinghamshire and Oxfordshire 1.6% 161.4 2.4% 3 Surrey, East and West Sussex 1.2% 114.2 0.3% 2	Shrophire and Staffordshire	0.8%	49.4	0.6%	2.2
Bedfordshire and Hertfordshire 4.1% 110.4 0.3% 3 Essex 3.3% 34.3 0.1% Inner London 0.2% 198.4 0.04% 1 Outer London 0.8% 109.1 0.03% Berkshire, Buckinghamshire and Oxfordshire 1.6% 161.4 2.4% 3 Surrey, East and West Sussex 1.2% 114.2 0.3% 2	West Midlands	0.3%	149.6	0.2%	8.2
Essex 3.3% 34.3 0.1% Inner London 0.2% 198.4 0.04% 1 Outer London 0.8% 109.1 0.03% Berkshire, Buckinghamshire and Oxfordshire 1.6% 161.4 2.4% 3 Surrey, East and West Sussex 1.2% 114.2 0.3% 2	East Anglia	9.1%	72.1	1.4%	4.4
Inner London 0.2% 198.4 0.04% 1 Outer London 0.8% 109.1 0.03% Berkshire, Buckinghamshire and Oxfordshire 1.6% 161.4 2.4% 3 Surrey, East and West Sussex 1.2% 114.2 0.3% 2	Bedfordshire and Hertfordshire	4.1%	110.4	0.3%	33.5
Outer London 0.8% 109.1 0.03% Berkshire, Buckinghamshire and Oxfordshire 1.6% 161.4 2.4% 3 Surrey, East and West Sussex 1.2% 114.2 0.3% 2	Essex	3.3%	34.3	0.1%	3.6
Berkshire, Buckinghamshire and Oxfordshire Surrey, East and West Sussex 1.6% 161.4 2.4% 3 114.2 0.3% 2	Inner London	0.2%	198.4	0.04%	19.0
Surrey, East and West Sussex 1.2% 114.2 0.3% 2	Outer London	0.8%	109.1	0.03%	4.5
·	Berkshire, Buckinghamshire and Oxfordshire	1.6%	161.4	2.4%	37.1
TI 1' III CYY'I.	Surrey, East and West Sussex	1.2%	114.2	0.3%	20.4
Hampshire and Isle of Wight 1.6% 34.9 0.5% 1	Hampshire and Isle of Wight	1.6%	34.9	0.5%	10.2
Kent 0.1% 193.1 0.2%	Kent	0.1%	193.1	0.2%	7.3
Gloucestershire, Wiltshire and Bristol/Bath area 8.7% 93.0 1.6% 3	Gloucestershire, Wiltshire and Bristol/Bath area	8.7%	93.0	1.6%	30.9
Dorset and Somerset 6.2% 68.7 1.5%	Dorset and Somerset	6.2%	68.7	1.5%	8.0
Cornwall and Isles of Scilly 3.7% 139.9 0.4% 1	Cornwall and Isles of Scilly	3.7%	139.9	0.4%	10.9
Devon 0.5% 289.9 0.04%	Devon	0.5%	289.9	0.04%	7.2
West Wales and The Valleys 0.1% 2.7 0.1%	West Wales and The Valleys	0.1%	2.7	0.1%	1.4
East Wales 0.1% 30.8 0.2%	East Wales	0.1%	30.8	0.2%	1.3
Eastern Scotland 0.5% 27.1 0.1% 4	Eastern Scotland	0.5%	27.1	0.1%	42.1
South Western Scotland 0.8% 93.6 0.3% 2	South Western Scotland	0.8%	93.6	0.3%	21.5
North Eastern Scotland 0.8% 865.8 0.01%	North Eastern Scotland	0.8%	865.8	0.01%	5.9
Highlands and Islands 3.3% 10.3 0.01%	Highlands and Islands	3.3%	10.3	0.01%	0.6
Mean 1.9% 120.5 0.5%	Mean	1.9%	120.5	0.5%	9.7

R is the ratio of R&D expenditures to sales. *IA* is expressed in thousands GBP per worker.

Appendix D

The Common Correlated Effects Pooled (CCEP) estimator of Pesaran (2006) is written as:

$$TFP_{jt} = \alpha_0 + b'\mathbf{X}_{jt} + \sum_{j=2}^{N} d_j \eta_j + \sum_{t=2}^{T} \sum_{j=1}^{N} \psi_{1j} (\overline{TFP}_t \eta_j) + \sum_{t=2}^{T} \sum_{j=1}^{N} \psi_{2j} (\overline{\mathbf{X}}_t \eta_j) + \mathbf{u}_{it}$$

The first three terms on the right-hand side represent a standard fixed effects estimator, \mathbf{X} is a vector of covariates and η is a set of cross-section specific dummies. Terms four and five in the summations capture cross-sectional dependence through interaction terms of cross-section averages of TFP and \mathbf{X} with a set N of cross-section specific dummies at time t (Pesaran, 2006; Eberhardt, Helmers & Strauss, 2013). Parameters to be estimated are: $\alpha_0, b', d_j, \psi_1$ and ψ_2 .

Table D1: TFP Levels in UK Regions and Firm Characteristics, 2004-2012, Within Fixed Effects Estimates (WFE)

	WFE	WFE
	(1)	(2)
HC	0.43**	0.161*
	(2.17)	(1.88)
$\overline{R}_{\scriptscriptstyle MNE}$	0.01	0.005
	(1.27)	(0.86)
\overline{IA}_{MNE}	0.024***	0.02**
	(4.02)	(2.01)
$\overline{R}_{\scriptscriptstyle DOME}$	-0.01	0.009
	(1.08)	(1.01)
\overline{IA}_{DOME}	-0.017	0.005
	(1.05)	(0.08)
Absorptive Capacity		
$HC imes \overline{R}_{\scriptscriptstyle MNE}$		0.2*
		(1.67)
$HC imes \overline{IA}_{MNE}$		0.25**
		(2.22)
$HC imes \overline{R}_{\scriptscriptstyle DOME}$		0.015***
		(2.93)
$HC imes \overline{IA}_{DOME}$		-0.004
		(0.55)
Time FE	Yes	Yes
Region FE	No	No
Observations	324	324
Adjusted R^2		
Cross Sectional Dependence (CD) Test/p-value	69.58/0.00	67.22/0.00

Absolute t statistics in parentheses with * p < 0.10, ** p < 0.05, *** p < 0.01. Coefficients reported represent elasticities. WFE assumes spatially uncorrelated error terms. WFE estimates are unbiased but inefficient.

Table D2: TFP Levels (Market Power Unadjusted) in UK Regions and Firm Characteristics, 2004-2012

	CCEP	CCEP	LSDVC	LSDVC
	(1)	(2)	(3)	(4)
$TFP_{t\text{-}1}$			0.143***	0.093***
$\overline{R}_{\scriptscriptstyle MNE}$	0.084^*	0.126	(3.34) 0.386***	(2.58) 0.080
\overline{IA}_{MNE}	$(1.80) \\ 0.018^*$	(0.55) 0.081***	(13.12) 0.016**	(0.43) 0.184***
\overline{R}_{DOME}	(1.89) 0.016**	(6.33) 0.152*	$(1.98) \\ 0.009^*$	(10.07) 0.162***
TA _{DOME}	(1.99) 0.004	(1.87) -0.119	(1.88) -0.016**	(2.87) -0.132
\overline{R}_{MNE}	(1.20) -0.014**	(0.97) -0.154	(2.44) 0.003	(1.24) -0.041
	(2.43)	(0.68)	(0.30)	(0.30)
	Interac	tion Terms-Absorptiv	ve Capacity	
$HC imes \overline{R}_{\scriptscriptstyle MNE}$		0.238***		0.234***
$HC imes \overline{IA}_{MNE}$		(6.22) 0.160*		(10.05) 0.169***
$HC imes \overline{R}_{\scriptscriptstyle DOME}$		(1.91) 0.031		(2.97) 0.034
$HC imes \overline{IA}_{DOME}$		(0.85) 0.049		(1.06) 0.016
		(0.75)		(0.41)
Time FE	No	No	Yes	Yes
Region FE	Yes	Yes	Yes	Yes
Observations Adjusted R^2	324	324	288	288
Aujusieu A	0.9805	0.6103		

Absolute t statistics in parentheses with * p < 0.10, ** p < 0.05, *** p < 0.01. Coefficients represent elasticities. Firm characteristics are in intensity ratios. CCEP corrects for cross-sectional dependence in the errors across regions and group-wise heteroscedasticity. Coefficients of cross-sectional averages with region dummies in CCEP are not reported as they have no economic interpretation. The LSDVC calculates biased corrected LSDV estimates (Kiviet, 1995).

Table D3: TFP Levels in the UK with Adjusted Firm Characteristics, 2004-2012

$\begin{array}{c ccccccccccccccccccccccccccccccccccc$
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$
$\begin{array}{cccccccccccccccccccccccccccccccccccc$
HC 0.82^{***} 0.217^{***} 0.18^* 0.159^{**} 0.187^* 0.290^{***} (4.54) (5.13) (1.91) (2.18) (1.74) (2.59) \tilde{R}_{MNE} 0.091^{***} 0.41^{**} 0.231^{***} 0.13^{***} 0.504^{**} 0.238^{**} (3.60) (2.49) (4.01) (5.15) (2.41) (2.43) $\tilde{I}A_{MNE}$ 0.016^{**} 0.085 0.011 0.057 0.028 0.095 (2.54) (0.28) (1.24) (1.01) (0.25) (0.76) \tilde{R}_{DOME} 0.055 0.202 0.030 0.691^{***} 0.064 0.18^{**} $\tilde{I}A_{DOME}$ -0.015 0.035 -0.072^{**} -0.159 -0.029 -1.254 (0.43) (1.44) (2.15) (0.76) (0.69) (1.22)
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$
$ \widetilde{R}_{DOME} = \begin{pmatrix} (2.54) & (0.28) & (1.24) & (1.01) & (0.25) & (0.76) \\ 0.055 & 0.202 & 0.030 & 0.691^{***} & 0.064 & 0.18^{**} \\ (1.35) & (1.64) & (0.56) & (6.30) & (0.23) & (2.01) \\ \widetilde{IA}_{DOME} = & -0.015 & 0.035 & -0.072^{**} & -0.159 & -0.029 & -1.254 \\ (0.43) & (1.44) & (2.15) & (0.76) & (0.69) & (1.22) \\ \hline $
$\widetilde{R}_{DOME} = \begin{pmatrix} (2.54) & (0.28) & (1.24) & (1.01) & (0.25) & (0.76) \\ 0.055 & 0.202 & 0.030 & 0.691^{***} & 0.064 & 0.18^{**} \\ (1.35) & (1.64) & (0.56) & (6.30) & (0.23) & (2.01) \\ \widetilde{IA}_{DOME} = \begin{pmatrix} -0.015 & 0.035 & -0.072^{**} & -0.159 & -0.029 & -1.254 \\ (0.43) & (1.44) & (2.15) & (0.76) & (0.69) & (1.22) \end{pmatrix}$
$\widetilde{IA}_{DOME} = \begin{pmatrix} (1.35) & (1.64) & (0.56) & (6.30) & (0.23) & (2.01) \\ -0.015 & 0.035 & -0.072^{**} & -0.159 & -0.029 & -1.254 \\ (0.43) & (1.44) & (2.15) & (0.76) & (0.69) & (1.22) \end{pmatrix}$
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(0.43) (1.44) (2.15) (0.76) (0.69) (1.22)
Interaction Torms, Absorptive Conseity
Interaction Terms-Absorptive Capacity
$HC \times \tilde{R}_{MNE}$ 0.2** 0.04*** 0.794**
(2.47) (8.63) (2.32)
$HC \times \widetilde{IA}_{MNE}$ 0.002 0.035 0.025
(0.23) (1.63) (0.89)
$HC \times \widetilde{R}_{DOME}$ 0.087* 0.062*** 0.071***
(1.87) (6.52) (3.02)
$HC \times \widetilde{IA}_{DOME}$ -0.075 0.005 0.0426
(1.48) (0.37) (1.14)
Time FE No No Yes Yes Yes Yes
Region FE Yes Yes Yes Yes Yes Yes
N 324 324 252 252 288 288
Adjusted R^2 0.9943 0.9947 0.4113 0.3814
F-statistic 97.092 7051.080
Hansen/p-value 13.139/0.437 13.772/0.683
Anderson/p-value 26.858/0.02 29.902/0.038 Absolute t statistics in parentheses with *** p < 0.10 ** p < 0.05 *** p < 0.01 Coefficients

Absolute t statistics in parentheses with ***p < 0.10, **p < 0.05, ***p < 0.01. Coefficients represent elasticities. Firm characteristics are weighted measures accounting for the share of each firm in total regional sales for each group of firm as per our definition in (10). CCEP corrects for cross-sectional dependence in the errors across regions and group-wise heteroscedasticity. Coefficients of cross-sectional averages with region dummies in CCEP are not reported as they have no economic interpretation. GMM uses as instruments endogenous variables in t-2 and t-3 and cross-sectional dependence is controlled for with Chudik and Pesaran (2015) adjustment. Hansen is a test of the over-identification restrictions in GMM. The joint null hypothesis is that the instruments used are valid; uncorrelated with the errors. Anderson is a likelihood ratio test for under-identification of instruments; a rejection of the null indicates that excluded instruments are irrelevant so the equation is well identified. The LSDVC calculates biased corrected LSDV estimates (Kiviet, 1995).

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i See Criscuolo and Martin (2009) for a discussion concerning identification issues of MNEs and local firms in the UK.

ii See Frenz and Ietto-Gillies (2007) for a detailed discussion on the distinction between *multinationality* and *foreignness*.
iii We consider an aggregate labour input because the level of workers with higher educational attainment is used

ⁱⁱⁱ We consider an aggregate labour input because the level of workers with higher educational attainment is used separately as a determinant of TFP. This methodological approach is necessary for the measurement of absorptive capacity.

iv See Gaur and Lu (2007) for a similar definition.

^v We appreciate that control can be exercised with a lower shareholding than 50% and that DOMEs can themselves be MNEs and/or born global firms. Here we wanted to focus mostly on pure DOMEs so as to get a clearer distinction and delineation of the relative effects of domestic and foreign firms.

vi Appendix D shows a detailed formulation of CCEP estimator.

vii Investment in scientific knowledge and organisational structure is crucial for internationalisation (Harris & Li, 2009), which is endogenously determined in export oriented firms. On the other hand, the low amount of intangible assets is an inherited characteristic of DOMEs which in turn explains why their contribution in regional TFP is of secondary importance.