FDI MOTIVES AND HOST COUNTRY PRODUCTIVITY EFFECTS OF US MNEs

ABSTRACT

In this paper we investigate the productivity effects of technology seeking and exploiting FDI. Although the positive effects of technology exploiting FDI are fairly widely accepted, this is not the case for technology seeking FDI, due to its inherent "knowledge-absorbing" nature. Nonetheless, based on three arguments distilled from previous literature, we claim that the productivity effects of technology seeking FDI may indeed be expected to be positive, and are at least as likely to occur as those of technology exploiting FDI. Using a new industry-level dataset of US MNEs' subsidiaries, active in 14 OECD countries over the period 1987-2003, we find broad and consistent support for this claim.

Key words: Technology seeking, FDI, knowledge spillovers

JEL codes: F23, L22, O32

INTRODUCTION

The cumulative ambiguity in empirical results regarding the productivity enhancing effects of inward Foreign Direct Investment (FDI) or 'spillovers' has led scholars to start investigating such effects in more detail (Smeets, 2008). Some studies try to disentangle the knowledge diffusion channels through which such effects allegedly take place (Javorcik, 2004; Görg and Strobl, 2005), while others have considered the moderating role of factors such as the absorptive capacity of local firms (Girma, 2005; Girma and Görg, 2007) or the geography of inter-firm patterns of location (Barrios, Bertinelli and Strobl, 2007; Nicolini and Resmini, 2007).

A more recent stream of literature has approached the issue by acknowledging the fact that multinationals (MNEs) and their foreign subsidiaries are not homogenous, and as such may generate different (productivity) effects on host-country firms (Keane and Feinberg, 2005). In this vain, some authors have investigated the influence of differences in MNE ownership structures (Javorcik and Spatareanu, 2008), parent nationality (Buckley, Clegg and Wang, 2007*ab*) and market orientation (Girma, Görg and Pisu, 2008; Smeets and Wei, 2009).

One form of MNE heterogeneity that has to date received much less attention in the FDI spillover literature is that of heterogeneity in investment motives, and in particular the distinction between *technology seeking FDI* vis-à-vis *technology exploiting FDI* .[1] Various scholars have examined *inter alia* the characteristics of companies involved in these two types of FDI (Kuemmerle, 1999; Le Bas and Sierra, 2002; Cantwell and Mudambi, 2005; Berry, 2006) and the regional characteristics that attract these different FDI types (Cantwell and Piscitello, 2005; 2007). These studies find persistent differences between the two types of FDI, which suggests that their effects on their host-country environment may also differ.

Contrary to some recent contributions by Girma (2005) and Driffield and Love (2007), our main claim in this paper is that technology seeking FDI will generate positive productivity effects in the host country, and that the existence of these effects will be at least as likely as those of technology exploiting FDI. We support this claim by three arguments which can be discerned in the literature. These arguments relate to

[1] Two recent exceptions are Girma (2005) and Driffield and Love (2007).

the R&D intensity of technology seeking FDI, the characteristics of firms that engage in either FDI type, and the general nature of knowledge diffusion.

We then empirically test the relationship between technology seeking and exploiting FDI on the one hand, and productivity effects on the other, using a new industry-level dataset of the foreign activities of US MNEs in 14 OECD countries over the period 1987-2003. Our results are supportive of the expectation that technology seeking FDI is highly conducive to positive productivity effects in the host country, and moreover, that these effects arise more generally than those from technology exploiting FDI.

The rest of the paper is structured as follows: in the subsequent section we will review the literature on FDI motives, and spell out the four arguments that support our claim regarding the positive productivity effects of technology seeking FDI. Section 3 presents the data and the empirical methodology that we employ in this paper, and Section 4 reports the empirical results. Section 5 concludes the paper.

THEORY

FDI motives and productivity effects

The traditional literature on the MNE either implicitly or explicitly refers to the technology exploiting motive of Foreign Direct Investment (Hymer, 1976; Dunning, 1977). That is, in order to overcome its *liability of foreignness*, a MNE and its subsidiary have to possess some firm-specific competitive advantage in order to be able to compete with local (foreign) firms. This firm-specific advantage (Rugman, 1981) or nationality of ownership advantage (Dunning, 1958) has often been associated with a technological competence or asset (Markusen, 2001), which is capable of being transferred and thus exploited in other suitably advantaged locations.

Yet in more recent years, a complementary motive for FDI has been increasingly recognized, in which a MNE is argued to benefit from the international scope of its activities by seeking or sourcing technology-based assets from its foreign-located counterparts. The articulation within the firm of this MNE motive or strategy may be the initially unplanned outcome of the evolution over time of selected subsidiaries (Birkinshaw and Hood, 1998), that as they have matured have become increasingly capable of local initiatives, entrepreneurship and new business network creation (Birkinshaw, 1997; Forsgren, Holm and Johanson, 2005). This locally competence creating type of FDI has sometimes been termed technology seeking or asset augmenting FDI (Dunning and Narula, 1993; Kuemmerle, 1999; Le Bas and Sierra, 2002).

Inspired by the recent trend to examine more closely the interaction between MNE heterogeneity of motives and host-country locational characteristics, Girma (2005) and Driffield and Love (2007) study the extent to which these differing FDI motives generate different productivity effects in the UK. In both these studies, the distinction between technology exploiting and seeking FDI is based *inter alia* on relative R&D intensities (RDIs) between the home and the host country.[2] It is argued that since FDI with a technology seeking motive is aimed at seeking or sourcing technology in the host country in fields in which the MNE is lacking, it can reasonably be expected that the RDI of the home country-industry of the MNE is lower than that of the host country-industry, assuming that MNEs are at least on average representative of the areas from which they originate. Hence, if the ratio of home country RDI over host country RDI is less than one, FDI is defined to be of a technology seeking type. If it is greater than one, it is termed technology exploiting FDI.

Since technology seeking FDI (by definition or assumption) originates in terms of its country of ownership from less R&D intensive industries when compared to the equivalent industries in the host locations in which it is sited, it is hypothesized that technology seeking FDI will not induce any knowledge diffusion to local actors in the host country. The reverse holds for technology exploiting FDI, which is thus expected to induce positive knowledge diffusion, given the relative home country technological advantage. Both Girma (2005) and Driffield and Love (2007) find broad support for these hypothesized effects.[3]

In the remainder of this section we will question the basic premise behind this argument, i.e. that technology seeking FDI is characterized as that which runs between industries with home-host RDI ratios smaller than one. Our line of reasoning follows three alternative strands of thinking on this issue. The (expected) R&D

[2] RDI is measured as R&D expenditures as a percentage of value added (at the industry level).
[3] The study by Driffield and Love (2007) also makes an additional distinction based on whether or not there is an efficiency seeking motive for the FDI involved. Essentially, this efficiency seeking motive is expected to depress any positive diffusion effects of FDI because of the negative competition effects (based on lower host-country labor costs) it generates.

intensity of technology seeking FDI, the general firm characteristics of technology seeking firms, and the reciprocal nature of knowledge diffusion. We then formulate two hypotheses regarding the productivity effects of technology exploiting and seeking FDI.

Subsidiary mandates and R&D responsibilities

A recent and increasing microeconomic literature has investigated the relationship between subsidiary mandates (that may include either or both technology exploiting or seeking roles) and the corresponding R&D assignments or responsibilities that are likely to be received by the subsidiaries in question. Although such studies do not directly address the question of the productivity effects generated by MNE subsidiaries, they do shed some light on the extent and nature of R&D responsibilities of technology seeking affiliates.

Feinberg and Gupta (2004) investigate the determinants of R&D assignments by MNEs to their foreign subsidiaries, distinguishing between external (to the firm) and internal determinants of this decision. Among other factors, they argue and show that the extent to which the external host country environment provides knowledge spillover opportunities is positively related to the extent of R&D responsibilities assigned to subsidiaries in the host country. The argument here is that increased R&D at the subsidiary level allows the subsidiary to better absorb the external knowledge (Cohen and Levinthal, 1989; Minbaeva et al., 2003). It also implies that subsidiaries with a technology seeking mandate are more effective at acting on this mandate if they receive significant R&D responsibilities from the parent.

Cantwell and Mudambi (2005) investigate the relationship between the R&D responsibilities assigned to foreign subsidiaries, and the output mandates that such subsidiaries have received from their parents. In their sample of UK subsidiaries of non-UK MNEs, one thing that clearly stands out is the substantially larger RDI of subsidiaries with a competence creating mandate (CC), versus those with a competence exploiting (CE) mandate.[4] It should be noted that in their study a CC mandate refers to local subsidiary responsibilities for product development and international strategy development within their MNE group, and so is measured

[4] Specifically, in their Table 4(b) (p. 1120) they show an RDI (measured as a subsidiary's R&D over sales ratio) of 5.1% versus 2.9% of competence creating versus competence exploiting subsidiaries respectively.

independently of the R&D activities of a subsidiary. Moreover, their empirical tests also demonstrate that in addition to the observed quantitative difference in RDI between subsidiary types, there is also a qualitative difference in the motives for and hence in the nature of R&D undertaken. In particular, R&D assignments to CE subsidiaries are more sensitive to local demand conditions, whereas those of CC subsidiaries respond more to the level of regional development, resources, infrastructure and science base in the host location, a result which is further corroborated in Cantwell and Piscitello (2005; 2007).

Marin and Bell (2007) study the productivity effects of foreign subsidiaries located in Argentina in the period 1992-1996. To examine these effects, they propose *inter alia* an "active subsidiary model", in which knowledge spillovers to domestic firms arise only if subsidiaries are technologically active. Their empirical results provide strong support for this model, implying that knowledge spillovers from foreign subsidiaries mainly arise as a result of their own local competence creating and technology seeking activities.

Furthermore, a recent study by Phene and Almeida (2008) on foreign subsidiaries of US MNEs in the semiconductor industry adds to this result, as these authors demonstrate that subsidiaries with higher technology sourcing capabilities also engage in larger scale innovative efforts. In addition, their study finds consistent evidence of the importance of knowledge obtained from host country firms in stimulating subsidiary innovation. This would actually suggest a positive feedback effect, whereby CC subsidiaries obtain more R&D responsibilities, as a result they are able to source more knowledge from host country firms, and in turn they become even more innovative.

What all these studies clearly demonstrate is that the RDI of foreign subsidiaries with a technology seeking (or competence creating) mandate is not at all obviously lower than that of the host country firms active in the sector in which the subsidiaries are operating. The study of Cantwell and Mudambi (2005) also demonstrates that in comparison with CE subsidiaries, CC subsidiaries have a clearly larger RDI. As a consequence, technology seeking FDI is likely to generate positive productivity effects in its host-country environment. Additionally, given its greater RDI, such productivity effects are likely to be at least as large as, or even larger than those of technology exploiting FDI.

Firm heterogeneity and technology seeking FDI

A substantial amount of research has either implicitly or explicitly considered the nature or characteristics of the firms that engage in technology seeking FDI. In particular, the question of whether high-productivity (leader) or low-productivity (laggard) firms engage in this type of FDI has featured prominently in this debate. Many of the earlier empirical industry-level studies has suggested that laggards are more likely to engage in technology seeking FDI, as they stand to gain the most from it (Kogut and Chang, 1991; Hennart and Park, 1993; Neven and Siotis, 1996). This conclusion has also been formalized (Fosfuri and Motta, 1999; Siotis, 1999).

However, more recent microeconomic evidence suggests quite the contrary. Notably, in a study of Japanese investors in the United States, Berry (2006) convincingly demonstrates that leaders are more likely to engage in technology seeking FDI, a result which is corroborated *inter alia* by Le Bas and Sierra (2002), Branstetter (2006) and Griffith, Harrison and van Reenen (2006). Berry (2006) explains this finding by arguing that unlike leaders, laggard firms have neither the absorptive capacity nor the intra-firm technology transfer skills necessary to benefit from technology seeking FDI. Formalizing these arguments, Smeets and Bosker (2008) also demonstrate the likelihood of leaders engaging in technology seeking FDI, and provide an empirical illustration of this.

The implication of these more recent and more detailed studies on firm heterogeneity and FDI motives is that leaders, and not laggards, are more likely to engage in technology seeking FDI. Consequently, the implication is that in terms of spillover or diffusion potential, technology seeking FDI can be expected to generate at least as intense a level of productivity spillover effects in its host-country environment as does technology exploiting FDI.

The reciprocal nature of knowledge diffusion

A third reason to expect that technology seeking subsidiaries are as least as conducive to positive productivity effects as technology exploiting subsidiaries has to do with the alleged reciprocal nature of knowledge diffusion.

Already in 1989, Cantwell argued that in order to benefit from knowledge feedbacks, MNEs' subsidiaries have to internalize foreign technology development, which implies that their own operations have to be firmly embedded in the host-country environment. This in turn will generate larger knowledge diffusion potential from the subsidiaries to the host-country firms. As such, two-way knowledge diffusion is essentially just part of the logic of MNE expansion (Cantwell, 1989).

Frost (2001) makes a similar argument which he also formulates from an embeddedness perspective. He argues that the norm of reciprocity requires sufficient contributory innovative capacity on behalf of firms which themselves whish to capture external knowledge. Specifically, he claims that "subsidiaries with greater innovation scale may be more likely to access and utilize local sources of knowledge during the innovation process" (2001: 107). His empirical analysis of patent citations by a sample of US-based subsidiaries of foreign MNEs during the period 1980-1990 provides broad empirical support for this conjecture.

In a study of FDI in China, Wei, Liu and Wang (2008) substantiate this finding. Utilizing a 3SLS model to simultaneously investigate the knowledge diffusion effect from FDI to the host economy and vice versa, they find very strong and robust evidence of mutual (i.e. two-way) knowledge diffusion effects. This result again implies that when successful in technology seeking, subsidiaries are most likely to also diffuse some knowledge of their own. Similar findings are documented in Liu, Wang and Wei (2006).

These findings provide a third argument as to why technology seeking FDI may be at least as conducive to knowledge diffusion as technology exploiting FDI: It appears that in order for a subsidiary to benefit from knowledge spillovers generated by domestic firms – and as such perform its technology seeking task – it also needs to contribute to its local environment in terms of knowledge diffusion itself.

Summarizing, based on previous literature we have developed three arguments to support our claim of positive productivity effects of technology seeking FDI: the RDI of this type of FDI has been demonstrated to be substantial; recent microeconomic evidence indicates that high-productivity leader firms are more likely to engage in this type of FDI; and the demonstrated reciprocal nature of knowledge diffusion implies that technology seeking FDI is only successful when it also contributes to the productivity of its local environment.

From a methodological point of view, most of the microeconomic studies discussed above do not base the distinction between technology seeking and technology exploiting FDI on relative R&D intensities. E.g. Cantwell and Mudambi (2005) derive the competence creating motive of subsidiaries both from their outward orientation and the extent of new product development, independent of the R&D efforts of the subsidiary. Even though such an approach might be more complicated at higher levels of aggregation, this suggests that distinguishing between technology seeking and technology exploiting FDI should preferably go beyond the use of relative R&D intensities.

Also, we would like to note explicitly that we do not argue here that technology exploiting FDI does not generate productivity effects in the host country: since this type of FDI by definition exploits a competitive (technology) asset of the MNE, there is at least a potential for knowledge diffusion. Moreover, given that it will also be integrated in the local economy in terms of supplier and customer networks, there are also sufficient diffusion mechanisms present for this type of FDI (cf. Beugelsdijk, Smeets and Zwinkels, 2008). However, based on the foregoing we expect technology seeking FDI to be at least likely generating productivity effects as is technology exploiting FDI.

Thus, we end up with the following two hypotheses that we will investigate empirically in the remainder of this paper:

Hypothesis 1: Technology exploiting FDI will have positive host country productivity effects.

Hypothesis 2: Technology seeking FDI will have positive host country productivity effects that are at least as likely as those of technology exploiting FDI.

DATA & METHODOLOGY

FDI motives

In the empirical part of this paper we will try to illustrate our argument using industry level data of subsidiary activities of US MNEs in 14 OECD countries over the period 1987-2003.[5] We use industry-level data from the Bureau of Economic Analysis (BEA) in order to measure the activities of foreign affiliates of US MNEs. The BEA provides data regarding the operations of foreign subsidiaries on *inter alia* the amount

[5] The Appendix contains a full list of countries and industries included in the analysis.

of their annual sales, their net fixed capital stocks, the number of persons employed, and MNE R&D expenditures. As mentioned in the previous section, the distinction between technology seeking and technology exploiting FDI should preferably go beyond the use of relative R&D intensities. Using specific features of these data, we therefore try to improve upon the analyses of Girma (2005) and Driffield and Love (2007) in a number of ways.

First of all, subsidiaries that (successfully) pursue a technology seeking strategy can be expected to contribute to the knowledge and technology stock of the firm as a whole. Consequently, utilizing data on technology license receipts of foreign affiliates from their US parents, we are able to construct a measure of TS FDI (and TE FDI) which does not rely on the relative (home-host) RDIs as in Girma (2005) and Driffield and Love (2007). Specifically, if such receipts are positive, we assume that a subsidiary has engaged in some degree of competence creating or technology seeking activities. If technology license receipts are zero however, we assume the (dominant) activity was one of competence or technology exploitation.

Second, the discussion regarding the R&D intensity (RDI) of TS and TE subsidiaries in the previous section indicates that TS subsidiaries generally have a higher RDI than TE subsidiaries. Our data provide information on the R&D activities of the US subsidiaries in the relevant host countries, which we will use to construct RDIs as:

(1) $$RDI_{ijt} = \frac{MNE\_R\&D\_Exp_{ijt}}{MNE\_Sales_{ijt}}$$

where *i*, *j* and *t* index industry, host-country and time respectively, *MNE_R&D_Exp* is the R&D expenditure of the US MNEs' subsidiaries, and *MNE_Sales* are total sales of those subsidiaries. Consistent with the discussion in the previous section we expect TS FDI to be accompanied by a higher *RDI*. In the empirical specifications, we will consider several different thresholds for *RDI*.

Third, in order to enhance the comparison between our results and those of Girma (2005) and Driffield and Love (2007), we also construct relative RDIs (RRDIs) of the US MNEs' subsidiaries relative to the host-country sectors that they are active in:

(2) $$RRDI_{ijt} = \frac{RDI_{ijt}}{(R\&D\_Exp_{ijt} / Output_{ijt})}$$

where i, j, and t index industry, country and time respectively, *RDI* is as defined in (1), *R&D_Exp* is the industry-level R&D expenditure and *Output* is total industry-level output. Note that our measure improves on that of Girma (2005) and Driffield and Love (2007) by utilizing actual subsidiary R&D data instead of home-country industry-level R&D data. In line with the discussion on firm heterogeneity and technology seeking strategies in the previous section, we interpret *RRDI* <1 as an indication that the subsidiaries' activities are (relatively) lagging those of the host-country industry. In that case, FDI will not be of the TS type. When *RRDI* >1, FDI may be either of the TE or TS type.

Finally, our data allow us to consider the extent to which the host-country subsidiary activities are oriented towards foreign markets and towards the internal MNE network. Cantwell and Mudambi (2005) suggest that an international orientation is an important aspect of a CC or TS mandate. The reason is that by the time a subsidiary starts exporting, it has already earned a lot of autonomy and recognition in terms of capabilities and competence. Additionally, Smeets and Wei (2009) show that for TE FDI, the orientation of subsidiary activities is also an important element for the extent of knowledge diffusion.

The BEA data allow us to split up foreign affiliate sales into sales destined for the local market *versus* sales destined for exports (from the host country). We compute the relative shares of these two types of sales, and relate them to the extent of outward orientation of subsidiary activities:

$$\text{(3)}\qquad \begin{aligned} \text{local FDI}_{\text{ijt}} &= \frac{\text{local sales}_{\text{ijt}}}{\text{total sales}_{\text{ijt}}} \times FDI_{ijt} \\ \text{export FDI}_{\text{ijt}} &= \frac{\text{exports to other countries}_{\text{ijt}}}{\text{total sales}_{\text{ijt}}} \times FDI_{ijt} \end{aligned}$$

where i, j and t index industry, country and time respectively, and *FDI* is a measure of MNE presence: we use subsidiary capital stocks as the main variable and subsidiary employment for a robustness check.

As should be clear from the discussion in the theory section, the extent to which the subsidiary is integrated into the global MNE network is also an important aspect of a TS strategy. In order to get an indication about this extent of global integration, our data allow us to further disentangle *export FDI* as follows:

$$\text{(4)} \quad \begin{aligned} \text{parent FDI}_{\text{ijt}} &= \frac{\text{exports to US parent}_{\text{ijt}}}{\text{total sales}_{\text{ijt}}} \times FDI_{ijt} \\ \text{ROW FDI}_{\text{ijt}} &= \frac{\text{exports to Rest of the World}_{\text{ijt}}}{\text{total sales}_{\text{ijt}}} \times FDI_{ijt} \end{aligned}$$

Obviously, *ROW FDI* in (4) will also contain subsidiary exports to MNE affiliates in third countries, which also is an important indicator of the extent of intra-firm integration of the subsidiary activities. Unfortunately, the BEA data at the industry-level do not allow us to track these exports to other MNE affiliates. Finally, data on technology license payments and US MNE R&D expenditures (that we need to distinguish between TE and TS FDI) were also taken from the BEA and measured in millions of US dollars.

Empirical model

The model we wish to estimate takes the following form (with lower case letters denoting logs):

$$\text{(5)} \qquad \omega_{ijt} = \beta_0 + \boldsymbol{\beta}_1 \mathbf{FDI}_{\mathbf{ij,t-1}} + \boldsymbol{\beta}_2 \mathbf{X}_{\mathbf{ijt}} + \eta_i + \nu_j + \upsilon_t + \varepsilon_{ijt}$$

where *i*, *j* and *t* index country, industry and time respectively, ω is total factor productivity (TFP), **FDI** is a vector with the different types of FDI in period *t*-1 to take into account the lag between MNE activity and productivity effects, **X** is a vector of control variables, η, v and υ are fixed effects, and ε is an idiosyncratic error term. The parameters of interest are contained in the vector β_4 and measure the effect of the different types of FDI on industry productivity. We use two control variables in the vector **X**: (the log of) industry-level exports, measured in million of US dollars and also taken from the STAN database (*Exports*), and (the log of) industry-level R&D stocks, computed from data on R&D expenditures (from the OECD ANBERD database – *R&D*) using the perpetual inventory method and imposing a generic annual depreciation rate of 15% (Hall and Mairesse, 1995). Since industry-level exports also contain the exports of the US MNEs in our sample that we use in constructing the different FDI types, we net out those exports from the industry aggregate.

TFP (ω) estimates are derived as the residuals from loglinear Cobb-Douglas production functions that we estimate for each industry separately:

$$(6) \qquad y_{ijt} = \gamma_{0j} + \gamma_{1j} l_{ijt} + \gamma_{2j} k_{ijt} + \omega_{ijt}$$

where *i*, *j* and *t* index country, industry and time respectively, *y* is value added, *l* is labor and *k* is capital. The data for *y* and *k* are obtained from the OECD STAN database, and the data on *l* from the Groningen Growth and Development Center (GGDC). Value added and capital stocks are measured in million of US dollars, and the latter are computed from data on capital expenditures using the perpetual inventory method and imposing a generic annual depreciation rate of 5% (Hall and Mairesse, 1995). Employment is measured in thousands of total hours worked. We estimate (6) with Generalized Least Squares (GLS).[6] All variables have been deflated using industry-level GDP deflators. When appropriate, variables measured in foreign currencies have been transformed into US dollars using 1995 PPP exchange rates.

We follow Girma and Görg (2007) and assume that (the log of) *TFP* follows and AR(1) process with fixed effects (which are already included in model (5)):

$$(7) \qquad \omega_{ijt} = \rho\omega_{ij,t-1} + + \eta_i + \nu_j + \upsilon_t + \varepsilon_{ijt}$$

so that combining this process with the model in (5) yields the following empirical model:

$$(8) \qquad \omega_{ijt} = \beta_0 + \rho\omega_{ij,t-1} + \boldsymbol{\beta}_1 \mathbf{FDI}_{\mathbf{ij,t-1}} + \boldsymbol{\beta}_2 \mathbf{X}_{\mathbf{ijt}} + \eta_i + \nu_j + \upsilon_t + \varepsilon_{ijt}$$

This is the model that we will estimate. This model is not only analyzed for our total sample, but also for the different subsamples that result from our different operationalization of TE and TS FDI.

As mentioned above, our sample covers 14 OECD host countries and 8 manufacturing industries over the period 1987-2003. However, the panel is very unbalanced due to missing observations for many countries. Moreover, data on technology license payments were only available from 1994 onward, so that those

[6] There is a large microeconometric literature on the potential biases when estimating production functions like (6) without taking into account the possible correlation between inputs and productivity (Olley and Pakes, 1996; Levinsohn and Petrin, 2003). However, as noted by Bitzer, Geishecker and Görg (2008), such problems do not arise at the industry-level because output or value added can be argued to be stochastic at this level of aggregation. In this case, OLS or GLS of (6) leads to consistent estimates.

parts of the analyses using this variable use a limited sample. All variables have been deflated using industry-level GDP deflators.[7] When appropriate, variables measured in foreign currencies (in case of OECD data) have been transformed into US dollars using PPP exchange rates. Table 3 below presents some summary statistics and correlations for the variables in our model.

Method

In the empirical FDI knowledge diffusion literature, the potential endogeneity of FDI is a well-known problem: if foreign investors set up their subsidiaries in more productive countries, sectors or regions, any inferred productivity effects from FDI in model (8) will be spurious. Using lagged FDI variables could to some extent address this problem, however, this solution is less suited in situation where the series are persistent over time. Reverting to instrumental variable (IV) regression analysis would provide an alternative way out of this situation (Beugelsdijk et al. 2008), but such an approach is not straightforward in the present context: even though the gravity literature provides a number of potentially exogenous instruments for FDI (cf. Frankel and Romer, 1999), these mainly function at the country level rather than the industry level that we explore in this paper.

Additionally, the lagged dependent variable $\omega_{ij,t-1}$ captures dynamic adjustments of sectoral productivity. To the extent that productivity depends on its past realizations (e.g. due to learning effects or business cycles), its inclusion is important to control for "sluggish" adjustment of the productivity and to obtain unbiased coefficient estimates of the other explanatory variables (Baum, 2006). However, it again induces endogeneity since $\omega_{ij,t-1}$ is by definition correlated with the error term.

Under these circumstances, it is appropriate to revert to Generalized Method of Moments (GMM) estimation (Baum, 2006; Roodman, 2009). One specific estimator in this context is difference-GMM by Arrelano and Bond (1991) which transforms the model in (8) into first differences:

$$\Delta y_{ijt} = \hat{\rho}\Delta y_{ijt-1} + \hat{\boldsymbol{\beta}}_1 \Delta \mathbf{FDI}_{\mathbf{ijt}-1} + \hat{\boldsymbol{\beta}}_2 \Delta \mathbf{X}_{\mathbf{ijt}} + \Delta \upsilon_t + \Delta \varepsilon_{ijt} \quad (9)$$

[7] Although Kafouros and Buckley (2008) argue and demonstrate that the use of common deflators is not appropriate when dealing with R&D expenditures, we are not aware of more specific deflators for these countries and sectors on the scale used in our sample. As such, we use GDP deflators for R&D as well.

This removes the fixed effects in the error term, but it does not solve the endogeneity problem since $\omega_{ij,t-1}$ in $\Delta\omega_{ij,t-1}$ is now correlated with ε_{ijt-1} in $\Delta\varepsilon_{ijt}$. However, under the assumptions that the error term is not serially correlated and that explanatory variables are not correlated with *future* realizations of the error term, deeper lags of the explanatory variables are orthogonal to the error term, and hence may serve as proper instruments (cf. Carkovic and Levine, 2005). Thus the following moment conditions are used:

(10) $$E(\omega_{i,t-s} \cdot (\varepsilon_{it} - \varepsilon_{i,t-1})) = 0 \quad \text{s.t.} \quad s \geq 2; t = 3,...,T$$

$$E(FDI_{i,t-s} \cdot (\varepsilon_{it} - \varepsilon_{i,t-1})) = 0 \quad \text{s.t.} \quad s \geq 2; t = 3,...,T$$

To the extent that these explanatory variables are persistent over time or close to a random walk, lagged levels contain little information about future changes, and as such they will make weak instruments (Carkovic and Levine, 2005; Roodman, 2009).

Blundell and Bond (1998) solve this problem by extending the outlined approach to also include the levels equation in model (6), and using lagged differences – i.e. $\Delta\omega_{ij,t-1}$ and $\Delta FDI_{ij,t-s}$ – to instrument the endogenous variables *y* and *FDI*. These instruments are uncorrelated with the fixed effects in the error term, i.e.:

(11) $$E((\omega_{ij,t-s} - \omega_{ij,t-s-1}) \cdot (\eta_i + \nu_j + \varepsilon_{ijt})) = 0 \quad \text{s.t. } s \geq 1.$$

$$E((FDI_{ij,t-s} - FDI_{ij,t-s-1}) \cdot (\eta_i + \nu_j + \varepsilon_{ijt})) = 0 \quad \text{s.t. } s \geq 1.$$

For estimation purposes, the Blundell-Bond estimator builds a system of both models in (8) and (9) but treats them as a single-equation. As such, this estimator is called the system-GMM estimator, and it is adopted as it exploits more information in the data than the difference-GMM estimator alone.

Given the relatively limited amount of observations in our sample ($N = 547$ in the largest sample), we are forced to restrict the number of lags used in instrumentation to avoid over-fitting of the model (Roodman, 2009). Following Driffield and Love (2007), we first impose a maximum lag structure of 4 years.[8]

[8] Additionally, because our panel exhibits some gaps, instead of transforming the data using first differences we follow Roodman (2009) and use orthogonal deviations. This entails substracting the time-averaged value of all foregoing realizations of a variable instead of just its previous (one-period) observation (cf. Roodman, 2009: p. 20). This also implies that the AR test reported in Tables 2-4 are run on differenced residuals.

However, further inspection indicates that the error term in model (8) is autocorrelated up to AR(4), which renders the first four lags of the instruments for the endogenous variables in model (8) invalid. Hence, in the tables 2-4 below, we use lags 5-8 to instrument the endogenous variables. Moreover, we employ the one-step estimator. As Madariaga and Poncet (2007) argue, although the two-step estimator is more efficient, it is only appropriate in relatively large samples, otherwise it heavily biases the coefficient estimates. Finally, we utilize the small sample correction proposed by Roodman (2009), include time dummies in order to minimize the occurrence of contemporaneous (cross-section) correlation, and report robust standard errors.

Table 1 below presents some summary statistics and correlations for the variables in our model.

<< INSERT TABLE 1 ABOUT HERE >>

EMPIRICAL RESULTS

Local and export FDI

Table 2 below presents the system-GGM estimation results of the system of the models in (8) and (9), with subsidiary activities split into *local FDI* and *export FDI* as defined in (3). Column 1 of Table 2 presents the total sample results. The coefficient of lagged *TFP* is positive and significant, indicating positive feedback effects of productivity. R&D stocks and exports are also positive and significant, as expected. Both *local FDI* and *export FDI* contribute positively and significantly to host-country industry *TFP*, although the effect of the latter is somewhat larger and more significant. However, since we have not yet distinguished between TE and TS motives, these are essentially average effects. The test statistics at the bottom of the table demonstrate the existence of first-order autocorrelation – which is due to the inclusion of a lagged dependent variable – but from lag 5 onwards, the correlation in the error term disappears. This implies that our 5-8 period lagged instruments is indeed exogenous, which is confirmed by the Sargan-Hansen statistic, which is not significant.

<< INSERT TABLE 2 ABOUT HERE >>

Columns 2 and 3 split up the sample into those subsidiary activities that received a positive amount of technology license receipts – proxying TS FDI – and those that received none – proxying TE FDI – respectively. In both columns, *local FDI* has no significant productivity effects whereas *export FDI* shows up positively and significantly and with comparable coefficient estimates in both columns. This implies that both TS and TE FDI induce positive productivity effects, but only if subsidiary activities are sufficiently outward oriented.

Column 4 interacts both FDI variables with the R&D intensity (RDI) of the subsidiary activities, as defined by (1). As TS FDI is generally associated with a higher RDI, we expect the interaction term to be positive and significant. However, only the main effect of *export FDI* is significant in column 4; all the other (interaction) effects are insignificant.

In order to further investigate this unexpected result, columns 5-7 split up the sample into those subsidiary activities with RDIs above 25%, 50% and 75% of the total sample RDI distribution. Once again, *local FDI* is insignificant in all three columns. However, *export FDI* is positive and significant in column 5, with an increasing coefficient estimate and significance level in column 6. However, after restricting the sample to firms with RDIs above 75% of the sample-wide distribution in column 7, the effect of *export FDI* disappears. This may explain why the simple interaction between *export FDI* and *RDI* did not show up significantly in column 4, as it suggests the presence of a nonlinear relationship between the productivity effects of *export FDI* and the *RDI* of the related subsidiary activities.

Finally, columns 8 and 9 split up the sample into those activities with an *RRDI* <1 and >1 respectively, where *RRDI* is defined in (2). Since *RRDI* <1 essentially captures a sample of (relatively) lagging subsidiaries and their activities, we do not expect any productivity effects in column 8. The results are indeed consistent with this expectation. *Export FDI* in column 9 again shows positive productivity effects.

The other three variables – lagged TFP, R&D stocks and exports – essentially remain positive and significant in most of the specifications, except in columns 3 and 8. The test-statistics at the bottom of the table all indicate that the lagged levels and differences used to instrument the FDI variables are indeed exogenous.

Parent and ROW FDI

We further split up *Export FDI* into *Parent FDI* and *ROW FDI* as in (4), in order to investigate whether the integration of subsidiary activities into the MNE network has an important impact on the estimated productivity effects. Table 3 below presents the results.

As in Table 2, the coefficient estimates for *Local FDI* are largely insignificant, although it quite often shows up with a negative sign. Yet the distinction between *Parent FDI* and *ROW FDI* yields some interesting results.

In the total sample in column 1, the effect of both these FDI types is virtually indistinguishable. However, splitting up the sample according to the level of technology licence receipts in columns 2 and 3, we observe that only *Parent FDI* is positive and significant when these payments are positive, whereas only *ROW FDI* is positive and significant when these payments are absent.

When interacting the FDI types with the RDI in column 4, none of the main or interaction effects are significant. However, when we again split up the sample at the 25th, 50th and 75th percentile of the sample-wide RDI distribution in columns 5-7, the nonlinear pattern that we saw in Table 2 arises again. However, this only holds for *Parent FDI*; *ROW FDI* remains insignificant.

Finally, splitting up the sample according to the *RRDI* in columns 8 and 9, we again observe no effect of any of the FDI types in column 8. However, in the sample with *RRDI* >1 we see that only *Parent FDI* has a positive and significant productivity effect.

The other variables in general have the expected coefficient signs. Lagged TFP is always significant and the industry-level R&D stock mostly so. Exports contribute somewhat less significantly to productivity compared to Table 2. Moreover, the test statistics at the bottom of the table again indicate the validity of the instruments. All in all, the results in Table 3 clearly demonstrate the importance of further splitting up *Export FDI* into *Parent FDI* and *ROW FDI*.

Subsidiary employment

In their meta-study of empirical FDI knowledge spillover studies, Görg and Strobl (2001) find that the measure of MNE presence used has an important effect on whether or not productivity effects are found. Wei and Liu (2006) and Wei et al. (2008) combine this finding with a theoretical argument: they relate different measures of MNE presence to different knowledge diffusion mechanisms. Specifically, measuring MNE presence through capital stocks (as in Tables 2 and 3) will be good a proxy for diffusion through demonstration effects, whereas measuring it in terms of employment will generally be a proxy for diffusion through labor turnover. Given this potential importance of using different FDI measures, we repeat the analysis of Table 3 while using subsidiary employment levels as our measure of MNE presence. Table 4 presents the results. For reasons of space we only report the coefficient estimates of the FDI variables.

<< INSERT TABLE 4 ABOUT HERE >>

The most important finding of Table 4 is that the results regarding *Parent FDI* and *ROW FDI* are very much in line with those in Table 3, demonstrating the robustness of those results. The only exception is the fact that in the *RRDI* <1 sample in column 8, *ROW FDI* shows up with a (marginally) significant negative sign.

The comparison between Tables 3 and 4 is less favourable when considering *Local FDI*. In this case we see that using subsidiary employment as the FDI proxy renders many of the productivity effects of *Local FDI* negative and (marginally) significant in the specifications of columns 4, 8 and 9.

DISCUSSION & CONLCUSION

In this paper we have proposed that, contrary to recent empirical evidence, FDI motivated by a technology seeking strategy is at least as likely to induce positive productivity effects in the host country as technology exploiting FDI. We support this proposition by three arguments: first, a number of recent empirical microeconomic studies have demonstrated that the R&D and innovation intensity of MNE subsidiaries with a technology seeking mandate is substantial, and even likely to outperform that of technology exploiting subsidiaries. Second, there is increasing theoretical and empirical evidence that productivity leaders rather than laggards engage in technology seeking FDI, implying high knowledge spillover potential. Third, it has been demonstrated that productivity spillovers are most likely to be mutual, flowing not only from the MNE to domestic firms but also the other way around. This implies that to successfully seek technology, subsidiaries also have to be prepared to diffuse some of their own.

Based on these three arguments we hypothesize positive productivity effects of technology seeking FDI, also arguing that they are more likely to occur than those of technology exploiting FDI. We test these propositions, using data on US MNEs' foreign activities in 13 OECD countries and 8 industries over the period 1987-2003. In order to single out TS FDI, we employ several different methods: first, we consider foreign activities for which technology license receipts from the US parent were received. Second, we consider the mediating impact of the R&D intensity of the foreign activities. Third, we distinguish between activities with a *relative* (subsidiary-host industry) R&D intensity above and below 1. Along all these dimensions, we also consider the effect of a local *versus* an outward orientation of the foreign activities, as well as the extent to which they are integrated into the MNE network.

Overall, our results provide quite consistent support for our hypotheses, although the mechanisms seem to be more complex than existing theory would suggest. We find that innovative foreign activities (receiving parent technology license fees) induce positive productivity effects, but only for those activities that are sufficiently integrated into the global MNE network. As we have argued that these two elements are crucial elements of TS FDI, this provides clear support for our theoretical conjectures.

Theory also suggests that an increase in foreign R&D activity, as an important element of a TS strategy, leads to increased productivity effects. However, our empirical results demonstrate that this mechanism is not linear. Specifically, up to the 75th percentile, increased R&D intensity indeed induces (increasing) productivity effects. However, beyond the 75th percentile, this effect vanishes, suggesting that the relationship is non-linear. A plausible explanation is that beyond some critical level of R&D intensity, MNEs and their subsidiaries become more concerned with protecting (parts of) their firm-specific proprietary technology, even if this reduces the effectiveness of technology seeking. Moreover, again these results only occur for those activities that are sufficiently integrated into the wider MNE network.

In order to compare our results with earlier studies (Girma, 2005; Driffield and Love, 2007) we also consider the relative R&D intensity of foreign activities. In line with these earlier studies, we find that activities with relative intensities below 1 do not yield any productivity effects, whereas those with intensities above do. However, in contrast to those studies, we do not interpret these findings as evidence for productivity effects of TE FDI, since relative R&D intensities cannot distinguish between FDI motives, but only between leading and lagging activities. In that sense, these results tell us that leading US MNE activities induce productivity effects, whereas lagging activities do not. Yet again, we find that the former result only applies for those activities that are sufficiently integrated into the MNE network. As such, they seem to indicate that it is particularly the TS FDI of leading US MNEs that generate most productivity effects.

Finally, for TE FDI, the results are mixed. Overall we find no consistent effects of this type of FDI, as they vary substantially with the empirical specification and the proxy used to measure foreign subsidiary activities. There is a slight indication that FDI with an outward orientation (toward export markets) is somewhat more likely to generate productivity effects than FDI with a local market orientation.

Our results have a number of implications for future theoretical and empirical work. This study demonstrates the importance of heterogeneity in FDI motives for the observed productivity effects. Even though earlier theoretical and conceptual work has invested substantial effort in characterizing the differences between TS and TE FDI as well as the differences in their determinants, this literature has not yet brought together these different insights in order to clearly spell out their consequences for the host-country, e.g. in terms of productivity effects, and derive clear testable hypotheses for this. From a theoretical point of view, the game-theoretic literature on R&D decentralization decisions (Sanna-Randaccio and Veugelers, 2007) and FDI motives (Fosfuri and Motta, 1999; Siotis, 1999) provides useful building blocks to consider these issues in more formal detail.

Empirically, a clear limitation of the present study is its reliance on (rather aggregate) industry-level data, and the implication that we need proxies for FDI with technology exploiting and seeking motives, rather than more factual indicators (cf. Cantwell and Mudambi, 2005). We believe that there is a strong need for more empirical work using firm-level data and clearly distinguishing between investment motives. Given that many previous studies have already investigated many other aspects of these types of FDI at the firm-level, as indicated above, this should be a manageable avenue of future research.

Another limitation is the fact that our sample of host-countries is limited to OECD countries only. This is caused by the fact that detailed industry-level information on the dependent and explanatory (control) variables in our model are hard to come by for developing countries. However, it might be expected that the types of FDI differ substantially for developed *versus* developing countries, not only between exploiting vis-à-vis seeking FDI, but also within seeking FDI (efficiency seeking *versus* technology seeking). Including developing countries in the sample could substantially add to the variation in the FDI types and as such to the identification of the parameters in our model.

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Table 1: Descriptive statistics and pairwise correlations (N = 568)

	1.	2.	3.	4.	5.	6.	7.	8.	9.
1. Value added[a]	1.00								
2. Labor[a]	0.91	1.00							
3. Capital[a]	0.83	0.76	1.00						
4. R&D[a]	0.56	0.54	0.49	1.00					
5. Exports[a]	0.58	0.57	0.48	0.61	1.00				
6. Exploiting FDI	0.48	0.49	0.38	0.33	0.12	1.00			
7. Seeking FDI	-0.04	-0.10	-0.10	0.22	0.19	-0.40	1.00		
8. Home seeking FDI	-0.04	-0.09	-0.09	-0.03	-0.09	-0.03	0.34	1.00	
9. Other seeking FDI	0.01	-0.06	-0.06	0.24	0.24	-0.41	0.85	-0.29	1.00
Mean	9.30	5.19	10.3	8.08	9.21	3.48	2.71	0.37	2.19
s.d.	1.15	1.13	1.90	1.56	1.55	1.71	1.58	0.71	1.53

Table 2: Productivity effects of TE FDI and TS FDI – local and export FDI

	(1) Total Sample	(2) Tech License Pay > 0	(3) Tech License Pay = 0	(4) Interaction RDI	(5) RDI>25th percentile	(6) RDI>50th percentile	(7) RDI>75th percentile	(8) RRDI<=1 (stocks)	(9) RRDI >1 (stocks)
Lag TFP	0.962**	0.964**	0.977**	0.983**	0.964**	0.964**	0.994**	0.968**	0.974**
	(.032)	(.021)	(.032)	(.021)	(.018)	(.019)	(.045)	(.042)	(.016)
R&D Stock	0.025**	0.021**	0.023	0.026**	0.027**	0.036**	0.042†	0.020	0.015*
	(.008)	(.007)	(.014)	(.009)	(.010)	(.011)	(.022)	(.022)	(.007)
Exports	0.016*	0.016†	0.004	0.020*	0.019**	0.024**	0.065†	0.023	0.013
	(.007)	(.008)	(.025)	(.009)	(.008)	(.009)	(.033)	(.033)	(.008)
Local FDI	0.015*	0.015	0.012	0.000	0.004	0.012	0.001	-0.012	0.003
	(.007)	(.009)	(.008)	(.008)	(.010)	(.008)	(.009)	(.010)	(.005)
Local FDI * RDI				0.261					
				(.323)					
Export FDI	0.024**	0.028**	0.030**	0.020*	0.016†	0.023*	0.001	0.002	0.017*
	(.007)	(.010)	(.009)	(.010)	(.009)	(.011)	(.011)	(.012)	(.008)
Export FDI * RDI				0.124					
				(.574)					
Constant	0.163*	0.057	0.308**	0.148†	0.201*	0.205*	-0.068	0.364*	0.105
	(.075)	(.084)	(.109)	(.086)	(.082)	(.080)	(.157)	(.143)	(.066)
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-stat	143.4**	36.1**	240.0**	376.5**	374.0**	320.0**	69.0**	254.5**	722.6**
Hansen-test	42.3	24.5	27.7	38.9	34.4	23.2	17.8	1.61	21.1
AR1	-4.97**	-4.47**	-2.72**	-4.55**	-4.95**	-4.59**	-4.18**	-1.56**	-4.71**
AR5	-1.09	-1.56	-0.47	-1.24	-1.52	1.63	-0.94	1.35	-1.04
N	547	176	104	454	371	263	160	107	326

Notes: Dependent variables is (Log) Total Factor Productivity (TFP)
System GMM-estimates – One step robust estimator, lags >=5 used for endogenous variables
** 1% sig; * 5% sig; † 10% sig.

Table 3: Productivity effects of TE FDI and TS FDI – local, parent and ROW FDI

	(1) Total Sample	(2) Tech License Pay > 0	(3) Tech License Pay = 0	(4) Interaction RDI	(5) RDI>25th percentile	(6) RDI>50th percentile	(7) RDI>75th percentile	(8) RRDI<=1 (stocks)	(9) RRDI >1 (stocks)
Lag TFP	0.971**	0.973**	0.976**	0.961**	0.971**	0.970**	0.994**	0.949**	0.964**
	(.032)	(.021)	(.026)	(.038)	(.014)	(.021)	(.039)	(.040)	(.017)
R&D Stock	0.029**	0.006	0.022*	0.030**	0.024**	0.019*	0.038†	0.005	0.018*
	(.007)	(.009)	(.011)	(.011)	(.009)	(.009)	(.020)	(.017)	(.008)
Exports	0.013†	0.011	0.022	0.013	0.020**	0.021**	0.059†	0.018	0.023*
	(.008)	(.009)	(.014)	(.016)	(.007)	(.007)	(.035)	(.026)	(.009)
Local FDI	0.017*	0.003	0.015†	-0.003	-0.000	-0.002	-0.002	-0.020	-0.003
	(.008)	(.009)	(.008)	(.011)	(.008)	(.008)	(.009)	(.014)	(.008)
Local FDI * RDI				0.352					
				(.251)					
Parent FDI	0.028**	0.033**	0.067	0.032	0.017*	0.018**	0.002	0.019	0.021*
	(.006)	(.008)	(.051)	(.038)	(.006)	(.005)	(.012)	(.014)	(.008)
Parent FDI * RDI				-0.114					
				(3.36)					
ROW FDI	0.028**	0.010	0.021*	0.023	0.009	0.003	-0.005	-0.007	0.015
	(.009)	(.011)	(.009)	(.018)	(.009)	(.011)	(.011)	(.012)	(.001)
ROW FDI * RDI				0.139					
				(.571)					
Constant	0.194*	0.079	0.308**	0.250	0.170*	0.205*	-0.068	0.415**	0.012
	(.076)	(.099)	(.084)	(.165)	(.064)	(.080)	(.157)	(.115)	(.081)
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-stat	276.5**	919.1**	321.8**	389.9**	551.0**	378.9**	258.1**	795.8**	500.2**
Hansen-test	46.6	14.1	18.4	35.3	31.7	20.6	24.1	1.69	21.7
AR1	-4.99**	-4.51**	-2.63**	-2.95**	-4.88**	-4.58**	-4.38**	-3.54**	-4.30**
AR5	-1.04	-1.08	0.43	0.60	-1.51	-1.61	-0.94	1.56	0.44
N	547	176	104	454	371	263	160	107	326

Notes: Dependent variables is (Log) Value Added
System GMM-estimates – One step robust estimator, lags >=5 used for endogenous variables
** 1% sig; * 5% sig; † 10% sig.

Table 4: Subsidiary employment as a measure of MNE presence

	(1) Total Sample	(2) Tech License Pay > 0	(3) Tech License Pay = 0	(4) Interaction RDI	(5) RDI>25th percentile	(6) RDI>50th percentile	(7) RDI>75th percentile	(8) RRDI<=1 (stocks)	(9) RRDI >1 (stocks)
Local FDI	0.003	-0.012	0.008	-0.040*	-0.016	-0.012	-0.003	-0.046†	-0.016†
	(.013)	(.012)	(.014)	(.017)	(.010)	(.011)	(.020)	(.023)	(.010)
Local FDI * RDI				0.438					
				(.804)					
Parent FDI	0.032*	0.033*	0.125	0.030	0.025**	0.027**	0.008	0.033	0.036**
	(.012)	(.013)	(.087)	(.036)	(.007)	(.007)	(.022)	(.037)	(.010)
Parent FDI * RDI				2.04					
				(2.79)					
ROW FDI	0.024	0.006	0.031†	0.012	-0.004	-0.005	-0.005	-0.040†	0.012
	(.016)	(.016)	(.018)	(.030)	(.012)	(.015)	(.023)	(.021)	(.016)
ROW FDI * RDI				0.307					
				(1.12)					
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-stat	366.7**	1508.7**	840.7**	352.4**	444.3**	295.9**	61.4**	920.9**	687.1**
Hansen-test	45.4	20.4	19.9	32.4	28.3	25.6	19.7	2.15	24.2
AR1	-4.98**	-4.62**	-3.13**	-2.56**	-4.89**	-4.90**	-4.52**	-2.98**	-3.90**
AR5	-0.89	-1.22	-0.52	-0.26	-1.70	-1.09	-0.54	-0.52	0.23
N	550	176	106	455	371	263	160	107	326

Notes: Dependent variables is (Log) Value Added

System GMM-estimates – One step robust estimator, lags >=5 used for endogenous variables

** 1% sig; * 5% sig; † 10% sig.

Appendix

Table A.1: Sample countries & sectors

Countries	**Sectors**
Australia	Computers & electronic products
Belgium	Chemicals
Canada	Machinery
Denmark	Electrical equipment, appliances & components
Finland	Transportation equipment
France	Food & kindred products
Germany	Primary & fabricated metals
Ireland	Utilities
Italy	
Netherlands	
Norway	
Spain	
Sweden	
United Kingdom	