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Reverse Productivity Spillovers in the OECD: The Contrasting Roles of R&D and Capital

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Abstract

This paper analyzes the relationship between research and development (R&D) and capital investment by domestic firms and the productivity of foreign affiliates of multinational enterprises in developed countries. We explain why ‘reverse spillovers’ from domestic to foreign firms might differ when R&D and capital are considered as two separate channels. Using industry-level data for eight Organisation for Economic Co-operation and Development (OECD) economies (including the Czech Republic and Slovakia) in 2001–2007, we find robust evidence that R&D investment by local firms is positively associated with the productivity of affiliates of foreign firms. Our findings and theory add to the relatively scarce research on reverse spillovers and contribute to the literature on knowledge-seeking foreign direct investment (FDI).

Keywords: productivity spillovers, reverse spillovers, spillover channels, knowledge diffusion, research and development, foreign direct investment, technology sourcing, knowledge seeking

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Introduction

Global foreign direct investment (FDI) flows reached pre-global financial crisis levels of approximately US$1.5 trillion in 2013, and the United Nations Conference on Trade and Development (UNCTAD) projected them to approach U.S.$2 trillion annually in the next few years, with approximately half of the funds going to developed economies (UNCTAD, 2014). Developed countries hosted 39 percent of global FDI inflows in 2013 and accounted for 61 percent of the global FDI outflows in 2013 (UNCTAD, 2014). Whereas most studies on the host-country effects of FDI and FDI spillovers between foreign and local firms focus on developing and transition economies and the impact of FDI on local firms (Meyer and Sinani, 2009), this study focuses on the Organisation for Economic Co-operation and Development (OECD) and relatively understudied phenomenon of ‘reverse’ spillovers (Driffield and Love, 2003): i.e., how foreign affiliates’ productivity is related to and possibly affected by activities of local firms, in particular, their research and development (R&D) and capital investments.

Foreign affiliates account for approximately one-quarter of R&D and approximately 5–15 percent of capital expenditures and value added in both developed and developing countries (UNCTAD, 2012). They often learn from and interact with local enterprises in a virtuous, reciprocal manner (Wei, Lie and Wang, 2008; Eapen, 2012; Chung and Yeaple, 2008; Chen, Li and Shapiro, 2012; Alcácer and Chung, 2007). The aim of this study is to explain and analyze whether multinational enterprises (MNEs) benefit from R&D by local firms, and we contrast this with what we hypothesize are the potentially negative effects of capital expenditures by local firms on foreign affiliate productivity. By contrasting these two channels of FDI productivity spillovers, we build on the work by Tian (2007) on the role of tangible and intangible capital as two potential sources of FDI spillovers and contribute to the debate on the FDI motivation and
spillover effects (Driffield and Love, 2007; Cantwell and Smeets, 2013) by focusing on the
effects on foreign affiliates (not local firms) and channels of reverse spillovers. We also go
beyond country-level explanations of technology spillovers (Crespo, Martín and Velázquez,
2004; Fawaz and Moghadam, 2013) by focusing on industry and ownership differences.

The term ‘reverse spillovers’ has been coined and analyzed in the context of the United
Kingdom by Driffield and Love (2003), who have found that technology generated by the
domestic sector spills over to foreign MNEs but that this effect is restricted to relatively R&D-
intensive sectors. They also have found evidence that these spillover effects are affected by the
spatial concentration of industry (a point reinforced in a study of U.K.-based subsidiaries of non-
U.K. MNEs by Cantwell and Mudambi, 2011) and that learning-by-doing effects are restricted to
sectors in which technology sourcing is unlikely to be a motivating influence.

Driffield and Love (2003) claim that theirs was the first evidence of which they are aware
that reverse spillovers even exist. Earlier studies to explore the possibility of reverse knowledge
sourcing do not find strong support for it either in the developed countries (Kogut and Chang,
1991; Anand and Kogut, 1997) or in China (Buckley, Clegg and Wang, 2002). A recent United
Kingdom study by Fu (2012) does not find much evidence for reverse spillovers. That study
focuses on what Fu terms ‘managerial knowledge spillovers’ through the diffusion of
management practices and finds that reverse spillovers from local firms to MNEs from
industrialized countries appear to be limited despite significant spillovers of practices amongst
local firms. Her evidence from establishment-level panel data from the U.K. attests to the
existence and significance of intra-industry-, linkage-, and non-linkage-based, inter-industry
spillovers of managerial knowledge from foreign to local firms.

The evidence for reverse spillovers is also mixed for other developed countries. For
example, Scott-Kennel (2004) finds some survey evidence of positive reverse spillovers in New Zealand. However, a more recent study for New Zealand (Iyer et. al, 2010), based on the more extensive Longitudinal Business Database (2000–2007), finds no evidence for reverse spillovers (or for spillovers between foreign firms themselves). It does find, however, that domestic firms that export are able to appropriate backward and forward spillovers from foreign firms, but not horizontal ones. The result of spillovers between domestic firms in New Zealand is ambiguous. Conversely, Iyer, Stevens and Tang (2011) find some evidence of positive reverse spillovers of a (vertical) inter-industry nature, specifically finding that foreign affiliates are able to assimilate knowledge from indigenous suppliers in New Zealand.

A related emerging strand of research indicates the possibility of ‘mutual productivity spillovers’ between foreign and local firms and analyses these two-way spillovers in the context of China (Wei et al., 2008) and Eastern Europe (Franco and Kozovska, 2008). Wei et al. (2008) stress the role of indigenous technology and local knowledge that can diffuse and enable multinationals’ productivity enhancement and finds evidence of this phenomenon in one study that uses large-sample, firm-level econometric analysis and another study, a comparative case study, of seven companies in Chinese manufacturing. Franco and Kozovska (2008) focus on the role of clusters in mutual productivity spillovers. They find some evidence for reverse spillover effects both inside and outside clusters in Poland and Romania, even in low-tech sectors. They suggest that the presence of clusters could be a determinant in FDI localization decisions even if the host country does not possess higher technological capacity.

Below, we first develop hypotheses and then describe the empirical model, variables and data. Next, we present and discuss the empirical results and finally, we conclude the paper.
Theory and hypotheses

The theoretical debate on FDI spillovers acknowledged three positive ways in which FDI may affect local firms’ productivity (Görg and Strobl, 2001). The first effect is a competition effect: competition from MNEs may force domestic firms to increase their own competitiveness by updating their technologies and improving management techniques. The second positive effect is a linkage effect: Domestic firms may learn from observing MNEs when there are close business relationships (upstream or downstream) among them. The third effect of FDI is an employment effect: MNEs train their employees, who may later move to domestic firms with acquired skills. However, there are also negative effects. The market-stealing effect occurs when MNEs draw demand away from domestic firms and force them to cut down production (Aitken and Harrison, 1999). The skill-stealing effect, suggested by Girma, Greenaway and Wakelin (2001), occurs when MNEs attract the best workers away from domestic firms, leaving the domestic firms with lower-quality employees. Blomström and Kokko (1998) also acknowledge the role of demonstration and imitation effects in FDI spillovers.

For the most part, these considerations also apply to reverse spillovers. The competition effect applies to foreign entrants too, because there will be competitive pressures from local firms with home advantages. Until foreign companies learn about the local environment, this effect may even be negative in the short run. The linkage and employment effects can also apply to foreign investors. They can build linkages with and observe practices of local firms and can and most often do source workers from local firms. The negative market-stealing effect is likely to be more modest in reverse spillovers because foreign entrants usually arrive without having captured any existing market. The skill-stealing effect largely occurs only in the longer term after foreign entrants have acquired some workers, whom those firms may later lose to domestic
firms. There are usually few expatriate workers in foreign affiliates (as a share of total workers); thus, poaching of foreign staff by local firms is a minor issue. In general, it thus seems that the balance of these five core FDI spillover effects indicates positive reverse spillovers, but the exact result is worthy of empirical scrutiny.

Fosfuri and Motta (1999) and Siotis (1999) offer a more explicit economic theory of reverse spillovers, presenting formal models of the FDI decision that embody the possibility of technology sourcing. Driffield and Love (2003) build on these models that formally demonstrate how an investing firm that is a technological laggard will find it profitable to invest abroad despite an efficiency disadvantage, provided the probability of acquiring the leader’s technology through productivity spillovers is sufficiently high. Driffield, Love and Yang (2014) extend the theoretical discussion to include regional effects, hypothesizing that reverse spillovers occur principally within ‘triad’ regions (Europe, Asia and North America) rather than across them.

When we distinguish between R&D and capital as two distinctive channels of FDI spillovers, the theoretical predictions for reverse spillovers are not immediately clear. Tian (2007) claims that the direction of the effect of FDI technology spillovers through capital will depend on the combined effect of tangible and intangible assets of foreign invested enterprises on the productivity of local firms. He argues that it is difficult to protect the tangible assets of foreign enterprises, such as advanced equipment and production lines, from being observed and copied by domestic firms and thus, they are likely to generate a positive effect of technology spillovers on domestic firms’ productivity. In contrast, he argues that intangible assets—such as patents, copyrights, secret formulae and ingredients—are normally well protected from being ‘stolen’ by competitor firms and are thus unlikely to have much, if any, positive spillover effect on the productivity of (domestic) firms.
We disagree with Tian’s claim that it is only tangible capital that might have positive spillover effects, especially for reverse spillovers in the OECD context, and suggest a distinction between R&D and capital rather than intangible and tangible capital. Much of the ‘knowledge’ and ‘technology’ sourcing of foreign MNEs that establish operations in OECD is probably motivated by accessing R&D-related knowledge (Griffith, Harrison and Van Reenen, 2006) rather than tangible or intangible capital such as proprietary software and databases and firm-specific organizational competencies, including local competitors’ brand equity, which together account for majority of what is measured as intangible capital contribution to capital in OECD economies (Corrado, Hulten and Sichel, 2009; Van Ark et al., 2009). Conversely, Zámborský (2012a) analyses the host-country effects of FDI on productivity in the OECD and finds positive results for industries intensive in both R&D and other intangibles (such as marketing and management competencies).

By distinguishing between R&D and capital instead of tangible and intangible capital, we emphasize the ‘public good’ property of R&D (i.e., it is non-rivalrous and only partially excludable). Bloom, Schankerman and Van Reenen (2013), for example, indicate that the gross social returns to R&D are at least twice as high as the private returns. In spite of barriers to knowledge diffusion and the partly ‘tacit’ and ‘proprietary’ properties of R&D, there is a potential for that R&D investment by local enterprises will have a diffusion and positive impact on foreign affiliate productivity. It is also possible that local capital investment can have a negative competitive and market stealing effects, i.e., it can reduce foreign firms’ productivity. In the short run, there are strong barriers to imitation in FDI spillovers through intangible capital (Zhang, Li and Li, 2014), and foreign entrants will find it difficult to observe, copy or access the largely firm-specific capital and home-market knowledge of their local competitors. The result of
locals’ increased capital investments (with high private returns and low social returns) may be lower productivity of foreign affiliates due to lower demand drawn away by local firms. It is also possible that local firms in OECD will attract some skilled workers from foreign affiliates. In summary, by distinguishing between R&D and capital rather than between tangible and intangible capital, we were able to derive theoretical prediction for positive reverse spillovers from domestic R&D investment to foreign affiliate productivity. The following two testable hypotheses summarize our main theoretical arguments:

- **Hypothesis 1**: R&D investment by local enterprises in an industry will be positively related to the productivity of foreign enterprises in that industry.
- **Hypothesis 2**: Capital investment by local enterprises in an industry will be negatively related to the productivity of foreign firms in that industry.

**Empirical model and data**

Following prior productivity research (Hall, Mansfield and Jaffe, 1993), we estimate a log-linear Cobb-Douglas production function using value added (Y) of affiliates of foreign MNEs and real inputs for physical capital (K) and labor (L) for both domestic firms (d) and affiliates of foreign MNEs (f).

$$\log Y_{jct(f)} = \alpha + \beta_1 \log K_{jct(f)} + \beta_2 \log K_{jct(d)} + \beta_3 \log L_{jct(f)} + \beta_4 \log L_{jct(d)} + u_j + \mu_c + \iota_t + \epsilon_{jct} \quad (1)$$

K is capital formation and L is the number of workers, whereas c denotes country, j industry and t time (year). Variables $u_j$, $\mu_c$, $\iota_t$ are country-, industry- and time-specific effects. This framework has been used to estimate spillovers from FDI, i.e., the extent to which capital investment by foreign-owned firms is linked to total factor productivity in the domestic sector.
(Barrel and Pain, 1997, 1999; De Mello, 1999). The theoretical justification for this, derived from the theory of the firm, is that a technological advance (or technology new to a particular location) or the international transfer of firm-specific assets is embodied in new capital investment rather than in output, employment or local R&D expenditure. In an analogous argument, Driffield and Love (2003) state that in the case of reverse spillovers, the source of externality for the foreign-owned sector should take the form of capital investment in the domestic sector.

Other authors consider the role of domestic and foreign R&D investments on affiliate productivity in their estimation equations separately from capital (Lichtenberg and de la Potterie, 2001; Bitzer and Görg, 2009). Following this tradition and building on our earlier theory development, we augment equation (1) with R&D expenditure for both domestic firms and affiliates of foreign MNEs:

\[
\log Y_{jct(f)} = \alpha + \beta_1 \log K_{jct(f)} + \beta_2 \log K_{jct(d)} + \beta_3 \log L_{jct(f)} + \beta_4 \log L_{jct(d)} + \beta_5 \log R&D_{jct(f)} + \\
+ \beta_6 \log R&D_{jct(d)} + \nu_j + \mu_c + \iota_t + \varepsilon_{jct} \quad (2)
\]

Following Barrios and Strobl (2002), we also calculate foreign affiliates’ total factor productivity and use it as a dependent variable. Total factor productivity (TFP) is computed as:

\[
\text{TFP} = Y - a_K K - a_L L, \quad \text{where } Y \text{ is the level of value added, } K \text{ and } L \text{ are the level of capital formation and employment, respectively. The preceding variables are all expressed in logarithm while coefficients } a_K \text{ and } a_L \text{ represent the capital and labor compensation shares of value added, assuming } a_K + a_L = 1. \text{ We omit } K(f) \text{ and } L(f) \text{ from the right hand side in these specifications:}
\]
\[
\log \text{TFP}_{jct(f)} = \alpha + \beta_1 \log \text{K}_{jct(d)} + \beta_2 \log \text{L}_{jct(d)} + \beta_3 \log \text{R&D}_{jct(f)} + \beta_4 \log \text{R&D}_{jct(d)} + \nu_j + \mu_c + \iota_t + \epsilon_{jct}
\]  

(3)

Following Driffield and Love (2003) and Driffield and Love (2007), we also consider learning by doing in productivity growth and the cumulative effects of continuous production. This point was made by Islam (1995), who states that within an econometric framework, it is more pertinent to relate current total factor productivity to previous levels of output. This specification also avoids the problems of spurious results arising from employing external output. Therefore, a dynamic specification is employed in which accumulated experience is proxied by a lagged dependent variable:

\[
\log \text{Y}_{jct(f)} = \alpha + \beta_0 \log \text{Y}_{jct-1(f)} + \beta_1 \log \text{K}_{jct(f)} + \beta_2 \log \text{K}_{jct(d)} + \beta_3 \log \text{L}_{jct(f)} + \beta_4 \log \text{L}_{jct(d)} + + \beta_5 \log \text{R&D}_{jct(f)} + \beta_6 \log \text{R&D}_{jct(d)} + \nu_j + \mu_c + \iota_t + \epsilon_{jct}
\]  

(4)

In all specifications we also estimate a specification without domestic labor (Model 1 in our results) because there are no strong theoretical reasons for its impact on foreign affiliate productivity. The full specification including domestic labour is marked as Model 2.

The data source is the OECD, namely, the databases STAN Industry, STAN R&D Expenditure (ANBERD) and Foreign Direct Investment Statistics and Activity of Multinationals (see Table 1). The last-mentioned database provides data about affiliates of foreign MNEs with operations in the OECD. R&D is measured as R&D activities carried out by business enterprises, regardless of the origin of funding, whether for themselves or for others under contract. Until 2007, OECD STAN data accounted for research and development expenditures separately from
gross fixed capital formation, which included dwellings, buildings and structures, transport
equipment, other machinery and equipment, cultivated assets and intangible fixed assets,
including software and databases, mineral exploration and artistic and literary originals. The
intangible fixed asset share of total gross fixed capital formation in 2007 was three to 10 percent
for the countries in our sample, according to the OECD, with software and databases being the
main component of these assets (R&D and business competencies had not been included).
‘Insert Table 1 here.’

Overall, we have data for eight countries, 18 International Standard Industrial
Classification (ISIC) Revision three industries and seven years (2001–2007). However, the data
are not available for all years, industries and countries simultaneously. The data for all variables
were available for Austria (seven observations), the Czech Republic (84), Finland (31), Germany
(13), Italy (57), Norway (17), Slovakia (15) and the U.S. (55), in addition to the following 18
industries: mining and quarrying; food products, beverages and tobacco; textiles, textile
products, leather and footwear; wood and products of wood and cork; pulp, paper and paper
products; printing and publishing; chemical, rubber, plastics and fuel products; coke, refined
petroleum products and nuclear fuel; pharmaceuticals; rubber and plastic products; other non-
metallic mineral products; basic metals; fabricated metal products; motor vehicles, trailers and
semi-trailers; other transport equipment; aircraft and spacecraft; other manufacturing; and
electricity, gas and water supply. Although the number of all available observations for specific
variables ranges from 510 (domestic capital) to 877 (foreign labor), the number of observations
in which all variables are available drops to 178 in the main models because the data are not
available for all variables, years, industries and countries simultaneously. It drops further in
specifications that require lagged variables; therefore, the number of observations for countries
listed above does not total 178. Please see summary statistics for key variables in Table 2.

‘Insert Table 2 here.’

**Analysis and results**

We have initially estimated two specifications of equation (2) using ordinary least squares regression (OLS). The results indicated strong support for Hypothesis 1 and weak support for Hypothesis 2. The results of the Breusch-Pagan/Cook-Weisberg tests indicated no problems with heteroskedasticity of the error terms for the OLS results, indicating that there are no spurious sub-clusters of data that would reduce the statistical significance of coefficients. Then, applying the Hausmann-Taylor procedure indicated that a fixed effects regression is a more favorable method for empirical analysis relative to both random effects and OLS regression methods. We thus estimated the two models again using a generalized least squares (GLS) regression with fixed effects. The results again indicated strong support for Hypothesis 1. Coefficients for local R&D were 0.3 and statistically significant at the one percent level, and estimates for other variables were consistent with past studies. The results for Hypothesis 2 were not statistically significant in these specifications.

However, potential endogeneity is present in our model, particularly attributed to the relative direction of capital flows towards productivity between countries. Additionally, uncertain direction of such causality raises the potential of correlation between the independent variables and the error term. Moreover, invariant effects specific to foreign and domestic countries represented by unique geography and demographics are presently contained in the error term, highlighting the issue in which the explanatory variables are correlated with unobserved
country-specific effects. To solve these issues simultaneously instrumental variable method is employed initially.

We estimated two-stage least squares instrumental variable models that included TFP as dependent variable and included only (1) local R&D and foreign R&D and (2) local and foreign R&D and local capital as explanatory variables. The number of observations in these specifications was 279. In the first model, Hypothesis 1 was strongly confirmed at the one percent statistical significance level with a coefficient on local R&D of 0.364. In the second model, only the Hypothesis 2 was confirmed, with a coefficient of -0.057 on local capital (five percent statistical significance level). The internal instruments used in these estimations were not weak. However, diagnostic tests of these instruments revealed that they were correlated with the error term of the estimation. Moreover, the instruments were highly correlated with the explanatory variables across both model specifications. This in effect imposes threat to the validity of the instruments and is likely to bias OLS (instrumental variable) estimation.

Thus, to overcome this potential bias we have employed a dynamic panel with the Generalized Method of Moments estimator applied in first differences by transforming the level equation into first differences, and subsequently applying the lag of independent variable as instruments to control for endogeneity. More specifically, the Arellano-Bond method introduces lagged dependent variables into the specification that enables us to explore the productivity dynamics over time to control for autocorrelation. Additionally, a dataset of 8 countries and 18 industries compared to a time span of 7 years highlights the appropriateness of GMM estimation method as GMM fits data frame with large number of countries/industries and small number of years. Interestingly, dissecting the autocorrelation of the GMM sheds light on the lag structure of the model. It is only when the third lag is introduced that all moment conditions of GMM is
satisfied with non-rejection of the Sargan test of over-identification to ensure the validity of our instruments, and rejection of the first autoregressive component and non-rejection of the second autoregressive component. The moment conditions are not satisfied when the lag structure is less than three years. This indicates that the productivity dynamics is persistence up to three years. Table 3 presents the results of the Arellano-Bond test for lag selection for GMM instruments.

‘Insert Table 3 here.’

The GMM estimations of Equation 2 (see Table 4) offer results largely consistent with the OLS and GLS estimates, although the magnitude of the local R&D effects and statistical significance was somewhat reduced. We estimated one-step first-differenced GMM regressions of Equation 2 using a three-year lag of foreign productivity to reduce the endogeneity problem and to control for dynamic panel bias. This was the most appropriate method for our dataset, which had a small number of countries, thus disallowing the use of too many instrumental variables (such as in the system GMM). Hypothesis 1 was supported in the fully specified Model 2 and in Model 1 with domestic labor omitted, in both cases with coefficients on domestic R&D of 0.12 and statistical significance at the five to 10 percent level. Hypothesis 2 did not obtain support in any of the specified models. Both Models 1 and 2 exhibited reasonable, positive and statistically significant coefficients for foreign capital (0.4) and foreign labour (0.7–0.8). The diagnostics of the dynamic panel as revealed by the satisfaction of all moment confirms robustness of the results.

‘Insert Table 4 here.’

Finally, the results of the estimation with the lagged dependent variable (Equation 4) using the GMM method are presented in Table 5. The results for Hypothesis 1 were strongly confirmed at the five percent significance levels in this specification, with a coefficient of 0.219
for domestic capital in both the full specification (Model 2 in the table 5) and in the specification with domestic labour omitted (Model 1). The number of observations in these specifications was 148, however, and Hypothesis 2 was not supported. Both Models 1 and 2 exhibited reasonable, positive and statistically significant coefficients for foreign capital (0.4) and foreign labour (0.9). Again, with the satisfaction of all moment conditions against the GMM estimation highlights the robustness of the results.

‘Insert Table 5 here.’

**Discussion**

As in many econometric analyses, there is a question of endogeneity, selection bias and causality: Does local R&D investment lead to a higher foreign productivity, or do more productive foreign firms tend to locate in industries/countries with higher domestic R&D? MNE location choices may also be driven by the search for local companies with higher productivity. Previous studies have indicated that foreign MNE location choices are driven by local characteristics (McCann and Mudambi, 2004). Although we address the endogeneity issue by using the difference GMM estimation method with lags and introducing a lagged output variable into our empirical model, the answer to the direction of causality is not clear-cut and may be two-way. A number of studies indicate the fact that it is leading (i.e., more productive) firms that are more likely to engage in technology-seeking FDI. Berry (2006) indicated this in a study of Japanese investors in the U.S., a result corroborated by Le Bas and Sierra (2002), Bransletter (2006) and Griffith *et al.* (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. Smeets and Bosker (2011) formalized these arguments and demonstrated the likelihood of leaders engaging in technology-seeking FDI.
There is also an interesting issue of cross-country, industry and year variations in the results. Our analysis has not revealed substantial differences among year effects. Industry variation was largely captured by the R&D and other major estimation variables. However, there was one notable result for country effects. The results for the U.S. were weaker compared to a more consistent support for reverse spillovers in Europe. This is somewhat puzzling because the U.S. accounted for approximately 41 percent of the OECD’s R&D expenditures in 2008 and spent close to three percent of its GDP on R&D in 1999–2009, more than the OECD average of approximately two percent in that period. Interestingly, the weaker results for the U.S. disappear when we consider the specifications accounting for learning by doing (Equation 4 with lagged value added). That could mean the process of reverse spillovers occurs over time and that in countries with strong knowledge and IP protection, it may be necessary to invest substantially in accessing foreign knowledge before any potential spillover benefits to productivity occur (Grifffield et al., 2006).

It may also be the case that some countries’ FDI has a higher share of the ‘laggard’ knowledge-seeking FDI (such as from emerging-market multinationals). FDI by emerging-market firms may require more time and more building of absorptive capacity before any benefits to productivity occur. Andreff and Balcet (2011) provide a theoretical discussion of the recent trend of South-North FDI from emerging to developed markets. Van Den Bulcke (2012) documents the rising trend of Chinese multinationals investing in Europe rather than the United States. However, the European Commission (2012) indicates that in spite of the rising trend, the magnitude of FDI inflows from emerging economies to the EU remained relatively small compared to EU investors (60 percent) and the U.S. (approximately 22 percent) in 2010. Whereas the U.S. accounted for approximately 40.5 percent of non-EU FDI stock in the EU in
2010, China accounted only for approximately 1.2 percent (European Commission, 2012). U.S. FDI stock is also dominated by developed countries, with nine developed countries accounting for 83 percent of FDI stock in the U.S. in 2012, according to the U.S. Bureau of Economic Analysis; China ranked as only number 20 in FDI inflows to the U.S. in 2011–2012.

Interestingly, our results for Hypothesis 1 were strong for the relatively less R&D-intensive Czech Republic and Slovakia (which account for approximately one-third of our data). The Czech Republic’s R&D intensity was approximately one percent of its GDP in 1999–2009, and the Slovakian intensity was only 0.5 percent, compared to the OECD average of two percent in the same period. The results may be explained by the fact that leading foreign investors such as Volkswagen, PSA Peugeot Citroën, Sony and Panasonic in the Czech Republic and Slovakia tended to locate in industries in which local R&D and engineering traditions were strong, but they chose to continue to conduct much of their R&D in other locations. Srholec (2006) found that R&D intensity of local electronics firms in the Czech Republic was higher than R&D intensity of foreign entrants to the industry. Conversely, leading foreign investors such as PSA Peugeot Citroën in the Slovak car industry brought their most modern production technologies to their Slovakian plants, with PSA productivity levels in Slovakia surpassing those in firm’s other locations (Zámborský, 2012b). Although the technologies used by PSA in Slovakia were not developed there, Slovaks’ qualifications and knowledge has allowed them to absorb foreign know-how.

Overall, our results offer new evidence on positive reverse spillovers in a wider group of OECD countries. Although Driffield and Love (2003) were the first to find robust econometric evidence of reverse spillovers in the OECD, their study focuses on one country (U.K.), and other studies such as Fu (2012) find no evidence for reverse spillovers in the United Kingdom. A
recent study by Driffield et al. (2014) finds strong evidence for reverse technology spillovers in approximately 50 countries (both developed and emerging) but focuses on the regional nature of that investment rather than its channels. The emerging studies of ‘mutual spillovers’ between foreign and local firms (Wei et al., 2008 and Franco and Kozovska, 2011) find some evidence for spillovers but focus on emerging markets (China, Romania and Poland). Our study has included both long-standing OECD members (Austria, Finland, Germany, Italy, Norway and the U.S.) and new OECD members (the Czech Republic and Slovakia) and found an overall positive reverse spillover effect through R&D, whereas reverse spillovers through capital were negative or insignificant. Our results also offer some evidence for an underexplored possibility of knowledge-seeking FDI in the new OECD economies of the Czech Republic and Slovakia.

We extended Tian’s (2007) attempt to study the channels and sources of FDI spillovers. Whereas Tian (2007) distinguishes between tangible and intangible capital and theoretically and empirically suggests stronger FDI spillovers for tangible capital (in China), we offer alternative dual channels of R&D (with a higher potential for reciprocity) and capital (with a lower potential for reciprocity and potential negative competition effect) and find strong evidence for R&D as a conduit of reverse FDI spillovers in the OECD. In stressing the role of R&D as a channel of reverse spillovers, we differ from Driffield and Love (2003), who consider capital as a channel and use R&D only as a characteristic of the industry that affects spillovers. They split their sample into high- and low-R&D intensive industries and find support for positive FDI spillovers in the U.K. only in the high-tech sectors. By explicitly recognizing R&D as a conduit for technology transfer, we are more aligned with Lichtenberg and de la Potterie (2001) and Bitzer and Görg (2009), who include domestic and foreign R&D in their theoretical reasoning and estimation. However, they analyze R&D at the national level. We analyze it at the industry level.
Concluding remarks

This study contributes new evidence to the debates on reverse spillovers and knowledge-seeking FDI with a focus on developed countries, including the new OECD members (the Czech Republic and Slovakia). We find evidence for reverse spillovers from local firm R&D to foreign entrant productivity, whereas local capital investments have insignificant effects. Whereas outward FDI is still viewed with caution in some OECD policy circles and whereas some studies such as Bitzer and Görg (2009) indicate a negative impact of outward FDI on home country productivity, we demonstrate that outward FDI to OECD countries can be associated with the foreign affiliates’ higher productivity and potentially, with ultimate benefits for both the home and host countries of FDI. Our findings lend support to the conclusions of studies that offer evidence of positive outcomes of technology sourcing for the home country of FDI (Chen et al., 2012, Harhoff, Mueller and Van Reenen, 2014). We also add to the literature on mutual spillovers (Wei et al., 2008) by disentangling spillover channels beyond the conceptualization employed by Tian (2007).

Whereas studies that explicitly address reverse spillovers are rather sparse, the literature on knowledge-seeking FDI is larger and more established (Dunning and Narula, 1995; Kuemmerle, 1999; Le Bas and Sierra, 2002). The recent trend in this debate is to examine more closely the interaction between the heterogeneity of MNEs’ motives and host-country locational characteristics. Girma (2005) and Driffield and Love (2007) study the extent to which differing FDI motives generate different productivity effects in the United Kingdom. In both these studies, the distinction between technology-exploiting and technology-seeking FDI is based, inter alia, on relative R&D intensities between the home and the host countries.

Cantwell and Smeets (2013) challenge the basic premise of these studies, i.e., that
technology-seeking FDI is characterized as one that runs between industries with home-host R&D intensity ratios smaller than one. Their reasoning follows four strands of thinking: (1) the (expected) R&D intensity of technology-seeking FDI; (2) the general firm characteristics of technology-seeking firms; (3) the reciprocal nature of knowledge diffusion; and (4) the likely degree of competition effects of technology-seeking FDI. We built our theoretical argument primarily using element (4) and partly element (3) of their study by applying concepts of competition and market-stealing to our predictions about reverse FDI spillovers in the OECD and incorporating reasoning from studies on reciprocity of R&D knowledge diffusion.

Although our sample covers an interesting mix of long-standing OECD members (Austria, Finland, Germany, Italy, Norway, the U.S.) and new OECD members (the Czech Republic and Slovakia), it remains rather small. Some of the more interesting results (such as potential reverse knowledge spillovers and knowledge-seeking FDI in the Czech Republic and Slovakia and evidence for reverse spillovers in the U.S. when learning by doing are considered) need to be further corroborated in firm-level studies with larger samples for these countries. Motivations for FDI were also only indirectly considered in the empirical section of the paper.

In spite of its limitations, the paper has interesting implications for policy, strategy and further research. Whereas OECD policy makers have viewed both outward FDI from their home base and emerging outward FDI from developing countries (especially Brazil, Russia, India and China (i.e., the BRICs)) to the OECD with caution, our study indicates that foreign firms investing in OECD industries with relatively high R&D tend to be more productive. These firms eventually contribute towards approximately one-quarter of the R&D in their host countries and account for a significant share of domestic output, employment and exports. Their rising productivity should be viewed as a positive contribution to the domestic economy. The fact that
foreign affiliates seem to benefit from local R&D is also an evidence for wisdom of the Chinese ‘Going Out’ strategy and similar policies in other emerging nations, with growing evidence for international reverse spillover effects on parent firms from emerging-market MNEs invested in developed countries (Chen et al., 2012).

Overall, introducing the concept of ‘reciprocity’ in knowledge diffusion to the reverse FDI spillovers debate may offer a potentially optimistic view of FDI as a win-win endeavor whereby foreign firms both learn from and diffuse knowledge to local firms, and benefits from investment in R&D in particular accrue to both parties. It therefore may not be essential to require or expect foreign firms to conduct much R&D inside the host economy, because our study does not indicate much evidence for a positive effect of this effort on foreign (or indeed local) productivity (at least not in the short run). Knowledge may be often embedded in the local (home country) environment and flow in the first stage from the place where it is created to other firms, including the foreign affiliates in that country, only then trickling up globally to an MNE’s headquarters and worldwide subsidiaries. Productivity benefits from R&D conducted by foreign affiliates may not be immediate and direct and MNEs may consider knowledge sourcing from local (host country) R&D as a key component of their subsidiaries’ strategic mandates.

Further firm-level investigation of how exactly local R&D effort benefits foreign affiliate productivity and innovation capabilities and how reciprocity in R&D interactions works appears to be a fruitful avenue for future research. The global strategic management literature may be a good starting point in uncovering the exact motivations and mechanisms of knowledge-seeking FDI. Cantwell and Mudambi (2005), for example, tackle a related issue in their study of MNE competence creating and exploiting subsidiary mandates. Cantwell and Mudambi (2011) extend this analysis using the concept of ‘physical attraction’ and test their theoretical predictions
related to strategic deterrence of technology leaders and laggards on a large patent database.

Phene and Almeida (2008) study foreign subsidiaries of U.S. MNEs in the semiconductor industry, stressing the importance of knowledge obtained from host-country firms in stimulating subsidiary innovation. Chung and Yeaple (2008) also offer an interesting argument along this line of reasoning for U.S. multinationals’ international knowledge sourcing strategies.

Future research may also account for foreign MNEs’ entry modes. Foreign MNEs acquiring local companies might perform very differently from MNEs establishing greenfield operations in the host country. On the theoretical front, we would like to encourage more work in strengthening the implications of reverse spillovers for mutual productivity spillovers. It would also be worthwhile to improve the model of reverse spillovers with more explicit acknowledgement of their mediators and antecedents. Finally, other estimation methods, such as the Spatial Durbin Model, may be used to tackle the potential problem of endogeneity and the interaction among independent variables. Improved data from the OECD and other sources may also lead to an extended dataset with more observations and variables.
References


Bloom, N., M. Schankerman, and J. Van Reenen. 2013. “Identifying technology spillovers and


Economic Development, New Zealand. Available at:


## Appendices

### Table 1: Definitions of Variables.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Source</th>
<th>Period</th>
</tr>
</thead>
<tbody>
<tr>
<td>Y(f)</td>
<td>Value added of foreign affiliates</td>
<td>OECD Structural Analysis Database (STAN) and Activity of Multinationals</td>
<td>2001-2007</td>
</tr>
<tr>
<td>TFP(f)</td>
<td>Total factor productivity of foreign affiliates</td>
<td>OECD STAN and Activity of Multinationals (and authors’ calculations)</td>
<td>2001-2007</td>
</tr>
<tr>
<td>L (d)</td>
<td>Number of workers in domestic firms</td>
<td>OECD STAN</td>
<td>2001-2007</td>
</tr>
<tr>
<td>L (f)</td>
<td>Numbers of workers of foreign affiliates</td>
<td>OECD STAN and Activity of Multinationals</td>
<td>2001-2007</td>
</tr>
<tr>
<td>K(d)</td>
<td>Gross fixed capital formation of domestic firms</td>
<td>OECD STAN</td>
<td>2001-2007</td>
</tr>
<tr>
<td>K(f)</td>
<td>Gross fixed capital formation of foreign affiliates</td>
<td>OECD STAN and Activity of Multinationals</td>
<td>2001-2007</td>
</tr>
<tr>
<td>R&amp;D (f)</td>
<td>R&amp;D expenditures of foreign affiliates</td>
<td>OECD STAN, ANBERD and Activity of Multinationals</td>
<td>2001-2007</td>
</tr>
</tbody>
</table>

Notes: Data covers 8 countries (Austria, the Czech Republic, Finland, Germany, Italy, Norway, Slovakia and the United States) and eighteen ISIC 3-digit Rev. 3 classification industries.

### Table 2: Summary Statistics.

(for observations available for each of 8 variables and the 8 countries and 18 industries analyzed)

<table>
<thead>
<tr>
<th>Variable (logarithm)</th>
<th>Observations</th>
<th>Mean</th>
<th>Std. deviation</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ln Y (f)</td>
<td>765</td>
<td>8.174</td>
<td>2.307</td>
<td>1.000</td>
<td>14.853</td>
</tr>
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<td>Ln TFP (f)</td>
<td>682</td>
<td>0</td>
<td>1.061</td>
<td>-3.029</td>
<td>2.916</td>
</tr>
<tr>
<td>Ln L (d)</td>
<td>842</td>
<td>11.632</td>
<td>1.813</td>
<td>4.575</td>
<td>16.464</td>
</tr>
<tr>
<td>Ln L (f)</td>
<td>877</td>
<td>9.834</td>
<td>1.828</td>
<td>3.178</td>
<td>14.661</td>
</tr>
<tr>
<td>Ln K (d)</td>
<td>510</td>
<td>21.658</td>
<td>2.146</td>
<td>11.513</td>
<td>26.121</td>
</tr>
<tr>
<td>Ln K (f)</td>
<td>715</td>
<td>6.714</td>
<td>2.510</td>
<td>0</td>
<td>13.468</td>
</tr>
<tr>
<td>Ln R&amp;D (d)</td>
<td>590</td>
<td>20.705</td>
<td>3.645</td>
<td>12.356</td>
<td>30.131</td>
</tr>
<tr>
<td>Ln R&amp;D (f)</td>
<td>613</td>
<td>4.360</td>
<td>2.403</td>
<td>0</td>
<td>10.329</td>
</tr>
</tbody>
</table>

Notes: Not all of these variables were available simultaneously for all years, countries and industries.
Table 3: Arellano-Bond: Lag selection for GMM instruments.

<table>
<thead>
<tr>
<th>Dependent Variable logarithm of LnY(foreign)</th>
<th>Number of Lags</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1-2</td>
</tr>
<tr>
<td>Ln K (d) (domestic capital)</td>
<td>0.190</td>
</tr>
<tr>
<td>Ln K (f) (foreign capital)</td>
<td>0.211***</td>
</tr>
<tr>
<td>Ln L (f) (foreign labour)</td>
<td>0.980***</td>
</tr>
<tr>
<td>Ln R&amp;D (d) (domestic R&amp;D)</td>
<td>0.123**</td>
</tr>
<tr>
<td>Ln R&amp;D (f) (foreign)</td>
<td>0.0621</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Observations</th>
<th>Sargan test chi-squared</th>
<th>Sargan test (degrees of freedom)</th>
<th>Sargan test of over identification (p-value)</th>
<th>Arellano-Bond AR(1) p-value</th>
<th>Arellano-Bond AR(2) p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>178</td>
<td>178</td>
<td>178</td>
<td>178</td>
<td>0.00151</td>
<td>0.00222</td>
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<td></td>
<td>99.00</td>
<td>35.68</td>
<td>66.15</td>
<td>21.32</td>
<td>0.0765</td>
<td>0.0144</td>
</tr>
<tr>
<td></td>
<td>61</td>
<td>25</td>
<td>49</td>
<td>19</td>
<td>0.0517</td>
<td>0.00382</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.320</td>
<td>0.0107</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.0148</td>
<td>0.730</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.123</td>
<td>0.123</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.588</td>
<td>0.588</td>
</tr>
</tbody>
</table>

GMM Moment Conditions: Rejection of AR(1), Non-rejection of Sargan test, Non-rejection of AR(2) (Note* Yes, means satisfies all GMM conditions) No No No Yes
Table 4: Productivity Spillovers to Foreign Affiliates
First Differenced GMM Estimation in One Step (with 3-year lags)

<table>
<thead>
<tr>
<th>Dependent variable (logarithm of):</th>
<th>Model 1</th>
<th>Model 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ln Y(f) (foreign value added)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ln L (d) (domestic labor)</td>
<td></td>
<td>-0.087</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(-0.17)</td>
</tr>
<tr>
<td>Ln L (f) (foreign labor)</td>
<td>0.786***</td>
<td>0.736*</td>
</tr>
<tr>
<td></td>
<td>(3.09)</td>
<td>(1.70)</td>
</tr>
<tr>
<td>Ln K(d) (domestic capital)</td>
<td>0.073</td>
<td>0.058</td>
</tr>
<tr>
<td></td>
<td>(0.36)</td>
<td>(0.27)</td>
</tr>
<tr>
<td>Ln K(f) (foreign capital)</td>
<td>0.391**</td>
<td>0.394**</td>
</tr>
<tr>
<td></td>
<td>(2.57)</td>
<td>(2.39)</td>
</tr>
<tr>
<td>Ln R&amp;D (d) (domestic R&amp;D)</td>
<td>0.124**</td>
<td>0.124*</td>
</tr>
<tr>
<td></td>
<td>(2.03)</td>
<td>(1.99)</td>
</tr>
<tr>
<td>Ln R&amp;D (f) (foreign R&amp;D)</td>
<td>0.067</td>
<td>0.072</td>
</tr>
<tr>
<td></td>
<td>(1.33)</td>
<td>(1.22)</td>
</tr>
<tr>
<td>Observations</td>
<td>178</td>
<td>178</td>
</tr>
<tr>
<td>Sargan test chi-squared</td>
<td>21.32</td>
<td>21.08</td>
</tr>
<tr>
<td>Sargan test (degrees of freedom)</td>
<td>19</td>
<td>18</td>
</tr>
<tr>
<td>Sargan test of over-identification (p-value)</td>
<td>0.320</td>
<td>0.275</td>
</tr>
<tr>
<td>Arellano-Bond test for AR(1), p-value</td>
<td>0.011</td>
<td>0.011</td>
</tr>
<tr>
<td>Arellano-Bond test for AR(2), p-value</td>
<td>0.588</td>
<td>0.742</td>
</tr>
<tr>
<td>GMM Moment Conditions: Rejection of AR(1), Non-rejection of Sargan test, Non-rejection of AR(2) (Note* Yes, means satisfies all GMM conditions)</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Notes: p-value significance, * p<0.1, **p<0.05 and *** p<0.01
Figures in parentheses are t-statistics.
Table 5: Productivity Spillovers to Foreign Affiliates.
First Differenced GMM Estimation in One Step (with 3-year lags and lagged dependent variable)

<table>
<thead>
<tr>
<th>Dependent variable (logarithm of): Ln Y(f) (foreign value added)</th>
<th>Model 1</th>
<th>Model 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lagged Ln Y (f) (foreign value added)</td>
<td>-0.241**</td>
<td>-0.243**</td>
</tr>
<tr>
<td></td>
<td>(-2.10)</td>
<td>(-2.20)</td>
</tr>
<tr>
<td>Ln L (d) (domestic labour)</td>
<td></td>
<td>0.089</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.15)</td>
</tr>
<tr>
<td>Ln L (f) (foreign labour)</td>
<td>0.890**</td>
<td>0.942*</td>
</tr>
<tr>
<td></td>
<td>(2.40)</td>
<td>(1.69)</td>
</tr>
<tr>
<td>Ln K (d) (domestic capital)</td>
<td>0.172</td>
<td>0.184</td>
</tr>
<tr>
<td></td>
<td>(0.69)</td>
<td>(0.74)</td>
</tr>
<tr>
<td>Ln K (f) (foreign capital)</td>
<td>0.413**</td>
<td>0.411**</td>
</tr>
<tr>
<td></td>
<td>(2.02)</td>
<td>(2.03)</td>
</tr>
<tr>
<td>Ln R&amp;D (d) (domestic R&amp;D)</td>
<td>0.219**</td>
<td>0.219**</td>
</tr>
<tr>
<td></td>
<td>(2.15)</td>
<td>(2.20)</td>
</tr>
<tr>
<td>Ln R&amp;D (f) (foreign R&amp;D)</td>
<td>0.003</td>
<td>-0.003</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(-0.03)</td>
</tr>
<tr>
<td>Observations</td>
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<tr>
<td>Sargan test chi-squared</td>
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<td>15.54</td>
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<tr>
<td>Sargan test (degrees of freedom)</td>
<td>18</td>
<td>17</td>
</tr>
<tr>
<td>Sargan test of over identification (p-value)</td>
<td>0.623</td>
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</tr>
<tr>
<td>Arellano-Bond AR(1) p-value</td>
<td>0.041</td>
<td>0.031</td>
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<tr>
<td>Arellano-Bond AR(2) p-value</td>
<td>0.546</td>
<td>0.529</td>
</tr>
<tr>
<td>GMM Moment Conditions: Rejection of AR(1), Non-rejection of Sargan test, Non-rejection of AR(2)</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>(Note* Yes, means satisfies all GMM conditions)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: p-value significance, * p<0.1, **p<0.05 and *** p <0.01
Figures in parentheses are t-statistics.